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AFIT/GCA/LSQ/91S-10

A MODEL FOR ESTIMATING AIRCRAFT
RECOVERABLE SPARES ANNUAL COSTS

THESIS

Phillip L. Redding, Captain, USAF

AFIT/GCA/LSQ/91S-10

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AFIT/GCA/LSQ/91S-10

A MODEL FOR ESTIMATING AIRCRAFT RECOVERABLE SPARES ANNUAL COSTS

THESIS

Presented to the Faculty of the School of Systems and Logistics

of the Air Force Institute of Technology

Air University

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Master of Science in Cost Analysis

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Preface

There are a number of people who I am indebted to for their contributions to this thesis; but none have or deserve my gratitude more than my wife, Cindy. Without her patience and support throughout the entire process, the thesis would not have been possible. I'd also like to thank my son, Kyle, who gave up many hours with his Dad.

I owe a great deal of thanks to my advisor, Dr. Roland Kankey, for his guidance and support. Dr. Richard Murphy is largely responsible for everything I know about regression and so I guess I should thank him for my enlightenment to this almost mystical discipline. There were a number of people at HQ AFLC and ALD who were also very generous with their time and expertise--Capt Anne Dement, Mr. Ron Rosenthal and Mr. Roger Steinlegy were particularly helpful.

Finally, I would like to thank God for His guidance and forgiveness during this hectic period. I look forward to straightening out my scrambled priorities so that He and my family will once again receive the attention that they deserve.

Phillip L. Redding

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Abstract

This thesis covers three objectives: 1) a background reference document concerning recoverable spares cost estimating was developed; 2) a representative sample of existing spares cost models were evaluated; and 3) aircraft physical and performance characteristics were used to develop a model for estimating annual replenishment spares costs. The two-part model involved developing a condemnations cost estimating relationship (CER) first and then developing both a CER and spreadsheet generated factors which related condemnations to replenishment spares costs.

Four condemnation CERs were evaluated--one linear, one arithmetic transformation and two logarithmic transformation (both X and Y) CERs. Only the logarithmic transformations provided statiscally acceptable results, and even these models exhibited wide prediction intervals. This weakness was due to the large amount of variability in the CER databases (as evidenced by the number of outliers).

The CER relating condemnations to replenishment spares costs was a poorer statistical performer. Spreadsheet generated factors showed that the ratio of replenishment spares to condemnations requirements exhibited a downward trend across the data years--suggesting that the factors should be periodically re-validated. Mission design averages for fourteen weapon systems are also provided.

A MODEL FOR ESTIMATING AIRCRAFT RECOVERABLE SPARES ANNUAL COSTS

I. Introduction

General Issue

In the not too distant past, when new aircraft were being considered for development and production, logistics support "took a back seat" to considerations such as acquisition cost, schedule, and performance (Templin:21-22). Current Air Force policy now recognizes the need to consider logistical support throughout a weapon system's life cycle, from the earliest stage of concept exploration to final phase-out and disposal (TASC, 1989:Ch 5, 3). This change in emphasis is appropriate because operations and support (O&S) costs, at 60%, typically account for the largest share of a aircraft's total life cycle cost (TASC, 1989:Ch 5, 9). While political pressure is still great to reduce the acquisition costs of new aircraft, an underlying theme of this new emphasis on logistics support is that by spending more money up front to buy highly reliable/maintainable weapon systems, the Air Force can save money over the system's life cycle due to reduced O&S costs.

A major contributor to these O&S cost is the cost of recoverable spares (those which can be repaired when

broken). Several factors point to the need for improved spares cost prediction capabilities.

The first factor is the inadequacy of current cost models which can be used early in a weapon system's life cycle. Because cost estimates must be created for new weapon systems long before detailed maintenance plans and aircraft performance history are available, cost models used in the early design stage typically have limited input data and provide estimates only at highly aggregated levels (May, 1982:Ch 3, 5-6; TASC, 1989:Ch 5, 55). Cost estimating relationship (CER)-based models (also known as parametric models) are typically used during this stage. Even this early in the acquisition life cycle, however, important information concerning such factors as aircraft physical and performance characteristics are often evaluated for their cost impact. The problem lies in the fact that, historically, parametric spares models used at this stage have failed to include these important potential cost drivers (May, 1982:Ch 3, 3; Rexroad, Tillia, and Tritle, 1990:1). Because the models do not adequately explain what logically "drives" their estimates, they are difficult to defend. Additionally, since they are typically based solely on acquisition costs, any increases in design or production will indicate increased O&S costs. Thus, they can't be used to justify additional acquisition funds to save O&S funds. They provide inadequate insight into how cost changes in relation to the various design tradeoffs being evaluated.

Cost estimates are also required to support the development of spares budgets several years before the actual deployment of new weapon systems. The same situation described above applies here as well. The parametric cost models used to support the budget requirements provide no insight into what is driving the estimate. The requirements, therefore, are hard to defend and are subject to Congressional budget cuts.

Another cause for concern about current spares cost prediction capabilities is that HQ AFLC/FMBSR has recently transferred most of its responsibility for initial spares budget preparation to the Air Logistics Centers (ALCs) [FMBSR still budgets for common support equipment, a small percentage of the total requirement, and whole engine spares are handled separately]. The FY 92/93 Budget Estimate Submission (BES), dated September 1990, marked the first time that the ALCs were given this responsibility. Faced with this new task, the ALCs had many procedural questions for the previous estimators--HQ AFLC/FMBSR (Neuhart, 1991). Given the fact that FMBSR has been using a technique criticized for its exclusion of cost drivers (as described above), new techniques are desired (Rexroad, Tillia, and Tritle, 1990:1).

A final factor is the Defense Management Review Decision (DMRD) 904, dated 9 November 1989, which placed depot level repairable parts under a stock fund concept (LaGrone, 1990:Ch 1, 1). Under this concept, control of

obligation authority for recoverable spares will also be handed down from HQ AFLC to the individual ALCs. This should prompt much greater interest from the ALCs in obtaining new, more defendable cost estimating models for use, not only in the early acquisition stages, but over the entire life cycle of their weapon systems.

Specific Problem

A much criticized, yet common CER used to predict spares costs involves multiplying recurring aircraft flyaway costs by a spares "factor" (Dement, 1990:Sec 1; May, 1982:Chap 3,3: Rexroad, Tillia, and Tritle, 1990:1). The underlying logic of this model is limited to the assumption that the greater a weapon system's flyaway cost, the more expensive its spares will be. Potential cost drivers such as aircraft physical and performance characteristics are excluded. Parametric models which provide greater insight into underlying causal relationships are needed.

In addition to needing improved models for spares cost estimating, both DMRD 904 and the ALCs' new responsibility for estimating spares costs necessitate a greater understanding of the entire spares cost estimating process at management levels below the major command. As new personnel become involved in estimating spares costs for the first time, they will need a basic understanding of the factors they must consider and a familiarity with the current estimating techniques available. Although numerous

O&S cost models can be used to predict recoverable spares requirements, frequently organizations are familiar with their own model(s) but know little, if anything, about other available models. Research is needed to differentiate between the models and identify their appropriate uses.

Research Objectives

Given these serious deficiencies in the current recoverable spares cost estimating field, the objectives of this thesis are threefold:

1) A general overview of the entire recoverable spares cost estimating process will be provided for personnel new to this field.

2) A summary-level description of several currently available cost models applicable to recoverable spares will be provided.

3) Aircraft physical and performance characteristics will be evaluated as potential cost drivers to develop a new parametric model for estimating annual replenishment spares costs.

In satisfying these objectives there are a number of questions that will have to be answered:

1) How are recoverable spares currently managed?

2) What factors affect the cost of recoverable spares?

3) How do cost estimating techniques vary depending on the estimate's purpose and/or the aircraft's life cycle stage?

4) What are the purposes, algorithms, data inputs and sources, and underlying logic of the existing models?

Scope

The scope of this paper is limited to estimating the cost of recoverable spares. These spares can be defined as "repairable parts, assemblies, components, etc. used in the repair of higher level assemblies" (Reynolds, 1989:49). This excludes repair parts, which can be defined as "consumable, non-repairable parts used to repair higher level assemblies" (Reynolds, 1989:49). The following sentence uses these terms in context: "It may be cheaper to repair a broken 'spare' circuit board than to buy a new one, but it is never more economical to fix a broken 'repair part' such as a nut or a screw."

Additionally, the costs estimated are limited to peacetime operating stock (POS) requirements and therefore exclude War Readiness Material (WRM) calculations. The logistics support required during war time is very different than that needed in peace time and therefore the two scenarios require separate cost prediction models (Hoffmayer, Finnegan, Jr., and Rogers, 1980:5).

According to reliability theory (Gill, 1991:21-41), the number of component failures (and therefore condemnations) is higher early in a weapon system's life cycle due to manufacturing defects and higher later in the weapon system's life cycle due to wear out. This thesis is limited to predicting recoverable spares requirements during the time between these two extremes--when failure rates are, according to theory, fairly constant. In order to

II. Background

Introduction

To enhance readability, the general spares cost estimating overview and summary of existing cost models applicable to spares (research objectives one and two) are included as Appendix B and C to the thesis. Those readers who are new to spares cost estimating may want to read these appendices before proceeding. This chapter relates to the third research objective--development of a new spares CER. It begins by describing the selection of data used in the CER development. Following this, a brief justification for the use of the parametric estimating technique is provided and the assumptions of linear regression are addressed. Next, existing spares CERs are evaluated in an attempt to narrow down the list of cost driver candidates. Finally, a brief summary of the literature review is provided.

Data Selection

Perhaps one of the most difficult aspects of developing a good aircraft spares CER is obtaining an adequate database. This section begins by describing the problems associated with using obligation data as a dependent variable. Condemnation spares costs were chosen as an alternative dependent variable for a replenishment spares model and the rationale for this decision is discussed. Because condemnation costs do not equate exactly to

(called the dependent variable), to one or more other cost drivers (called the independent variables) (Ch 10, 3).

Cost Drivers - "Those [independent] variables that exhibit some systematic relationship with cost" (Ch 10, 3).

Flyaway Costs - Non-recurring plus recurring costs for airframe, propulsion and avionics, program management, test and evaluation, [and] allowances for engineering changes. (Levine and Horowitz, 1989:5)

Initial Spares - Repairable components which support newly fielded end items (or principal items) for the entire production run of the aircraft (Rexroad, Tillia, and Tritle, 1990:21).

Life Cycle Cost (LCC) - The total cost to the Government of acquisition and ownership of the system over its full life It includes the cost of development, acquisition, operation, support, and where applicable, disposal. (Ch 5, 33)

Obligation - As used in the Air Force program control community, funds are said to be "obligated" at that point in time when the contractual agreement between the Air Force and contractor is posted into the official accounting and finance records. "Obligations" are separate from "commitments" and "expenditures." The former takes place when a purchase request or other authorized commitment document is signed by the accounting and finance certifying official and the latter takes place when the Air Force actually pays the Contractor.

Operations and Support (O&S) *Costs* - Fixed and variable costs of personnel, material, facilities, and other items needed largely for the peacetime operation, maintenance, and support of a system during activation, steady state operation, and disposal. (Ch 17, 3)

Provisioning - The process of determining and acquiring the range and quantity (depth) of spares and repair parts, and support and test equipment required to operate and maintain an end item of material for an initial period of service. (Ch 5, 34)

Reliability - The probability that the system will satisfy the need for which it was intended in an acceptable manner, for a given period of time, when deployed and used under a given set of operating conditions. . . . Satisfactory performance describes

the level at which the item/system must perform; performance below this level is then considered "failure" even though the specific part/component has not broken or reached a zero performance level. (Ch 5, 16)

Replenishment Spares - Repairable components, assemblies, or subassemblies required to resupply initial stockage or increased stockage for reasons other than support of newly fielded end items. Replenishment would include additional stockage due to increases such as usage, readiness initiatives, and redeployment of end items. (Ch 17, 40)

II. Background

Introduction

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replenishment spares costs, the findings from previous studies of the relationship between these two cost categories is provided. Next, the problems associated with finding an alternative dependent variable for an initial spares model are discussed. Finally, the logic behind the independent variable candidates analyzed in the CER development is provided.

<u>Dependent Variable Data Problem</u>. The problem in spares cost model development most frequently mentioned in the literature is the lack of good data to validate the cost models (Alexander, Brookey, Erhart, Fulton, Hofmann, and Shutak, 1990:ch IX, 7; Dement, 1991; Levine and Horowitz, 1989:1; May, 1982:Ch 10, 5-6). The most commonly used dependant vaiiable for spares cost model development was actual spares obligations. Obligation data presents two general problems: 1) reliable data is hard to find, and 2) even if reliable data can be found, what "was obligated" is still a poor proxy for what "should have been obligated."

There were several reasons given for why finding reliable obligation data is judged "difficult to impossible" (Alexander, Brookey, Erhart, Fulton, Hofmann, and Shutak, 1990:Ch IX, 7). The current definition of initial spares (Rexroad, Tillia, and Tritle, 1990:21) has only been in existence since March 1985 when the Office of the Secretary of Defense provided the current interpretation. Until that time there was no formal definition. The common practice,

however, was to budget enough initial spares money (BP16) to cover the first two years' requirements after initial deployment of the weapon system; with subsequent spares funded by replenishment spares money. Because initial spares, as currently defined, now cover the entire production run of the weapon system, including any increased requirements for previously fielded systems (Neuhart, 1990), the mix of initial and replenishment spares funding has shifted. This definitional change makes it difficult to separate weapon system obligations over time between initial spares and replenishment spares.

Additional reasons cited for difficulty in finding reliable obligation data include:

> vast quantities of data at very detailed levels with few pre-existing levels of data aggregation other than the top ones; [and]
>
> separation of explanatory worksheet files from the quantitative data. . . . (Alexander, Brookey, Erhart, Fulton, Hofmann, and Shutak, 1990:ch IX, 7)

Once these difficulties are overcome one is still faced with the fact that "what was obligated" does not necessarily coincide with "what should have been obligated." Many cost model projections are based upon given values for independent variables such as the number of flying hours, maintenance factors, and part utilization rates (Rexroad, Tillia, and Tritle, 1990:7, 9, 11, 12, 14). Through these factors the cost estimate is, in effect, provided for and based upon a given demand/availability performance level.

However, flexibility is allowed and the "replenishment spares budget does not have to be expended in the same manner as it is justified" (May, 1982: ch 10, 6). The operational performance level used as the basis for the cost estimate may therefore not be achieved. The cost estimate could conceivably provide accurate estimates for the proposed performance level and still <u>not</u> resemble the actual obligation figures because of the difference between the proposed and achieved performance levels. In addition, switching obligations from one weapon system to another can be influenced by political considerations not envisioned in the cost model. Thus, the obligations' correlation to the cost estimate is greatly impaired (Dement, 1991).

Finally, it is hard to track obligations to actual usage of spares because: 1) the spares budgets are forecast two years before funds are actually obligated (due to budget cycle) for spares that won't be used for another two years (due to contractor delivery lead time) and 2) the obligation money budgeted for one fiscal year, say 1990, can be spent over three fiscal years (1990 - 1992) making it impossible to determine what spares are procured with what budget year's obligations (May, 1982; ch 10, 6) [Note that spares money will only be good for one year's obligation under the new stock fund concept but this problem still affects old data].

The end result of these data problems is that: 1) those cost models developed using obligation data as their

dependent variable impair the internal validity of their model and must ca at their results, or 2) cost models are developed based on logical relationships but never validated against actual data.

Initial Spares Data. Because of these problems with obligation data, an attempt was made to identify another suitable dependent variable. Historically, differences in the requirements development processes for initial and replenishment spares has made alternative dependent variable identification more difficult for initial spares.

In the replenishment spares arena, annual buy requirements are generated by the D041, "Recoverable Consumption Item Requirement System." These near term requirements are then used as inputs to a regression-based model known as the Air Logistics Early Requirements Technique (ALERT) which is used to develop Program Objective Memorandum (POM) requirements [the POM is a long range budget document]. This computerized process provides a central database of historical requirements that can be used as an alternative dependent variable data set.

The situation is different in the initial spares arena. Because the initial spares requirements process, governed by AFLCR 57-27, has to date been primarily a manual system, no central database of annual initial spares requirements exist. Without a central database, no methodology akin to ALERT has been developed for budget development purposes.

To develop a historical database, one would have to contact the numerous inventory management specialists and end article item managers at each of the Air Logistics Centers. It is these individuals who developed the initial spares requirements and, hopefully, kept records of their manual computations.

A computerized approach to developing initial spares requirements using computations similar to D041 is currently in systems validation test and is due to come on line by the end of the summer of 1991 (Horner, 1991). The new computerized system, known as the Initial Requirements Determination (IRD) system, will have the capability to store historical data and will be useful to future analysts. Given the time constraints of this thesis, this task was not attempted and therefore a CER for initial spares is not attempted.

Replenishment Spares Data. The central requirements database for replenishment spares made identifying an alternative dependent variable an easier task. A partial solution to the problem was found in "condemnation spares" costs. Current AF policy states that if the cost to repair a failed spare part exceeds 75% of the cost to purchase a new spare, the item is "condemned" (i.e., not repaired) (Novak, 1991). Condemnation spares, therefore, are those new spares purchased to replace the condemned spares.

Condemnation spares make for a better dependent variable in that they are not obfuscated by many of the

factors affecting total replenishment spares obligations. For example, an aircraft's annual condemnation spares costs (as maintained in the Weapon System Cost Retrieval System (WSCRS)) are the aggregated product of all its condemned parts multiplied by the latest purchase price on record for these parts. Although condemnations are only a part of the total replenishment spares requirement, they are, at least, a true indicator of spares usage. Additionally, the WSCRS condemnation costs for each fiscal year (FY) correspond directly to the condemnations requirements for the same FYs. Finally, condemnations spares requirements track logically to cost drivers such as aircraft performance and physical characteristics.

Alternatively, obligations take place acquisition lead time away (approximately two years) from the actual demand and are, therefore, only estimates of the true demand. Obligations are tracked by fiscal years just like condemnations; but, as mentioned before, because any given fiscal year's funds may be obligated over a three year time-frame, the obligations are much harder to track to the spares they purchase. Finally, like condemnations, obligations may logically track to aircraft performance and physical characteristics, but they are greatly influenced by other factors, such as political pressures, which aren't accounted for in the model (Dement, 1991).

It was stated that condemnation costs are just a partial solution to the replenishment spares dependent

variable data set problem. This is true because condemnations costs are just one segment of total replenishment spares costs. In a world with perfect predictive powers, the term "replenishment" spares would be completely accurate because all the factors affecting demand for spares would be known (e.g., flying hour programs, parts utilization rates, maintenance factors). Because (in this perfect world) the right number of initial spares would always be bought, the replenishment spares function would simply be to "replenish" those spares which are no longer economically repairable (condemnations). In reality, funds aren't always available to purchase the desired number of initial spares, mission requirements change, and actual performance histories show that maintenance factors need revision. The result is that sometimes the Air Force buys too many initial spares, sometimes too few. At other times, changes require the purchase of spares for other than replacement of condemnations.

Demand Volatility. All of these factors which make up the difference between condemnation spares costs and total replenishment spares costs drive what is known in the HQ AFLC/FMCA office as the "churn" or "demand volatility" factor. It (demand volatility) accounts for the fact that replenishment spares funds are used to purchase additive requirements and (on occasion) pipeline spares requirements. The "churn" factor used in FMCA's Logistics Support Cost (LSC) model is 2.15 (Novak, 1991). This value is multiplied

by the condemnation spares cost generated by the model to arrive at the total replenishment spares cost.

The condemnation costs were identified as being a partial solution to the dependent data set problem because demand volatility must be accounted for before a total replenishment spares cost can be predicted. To complete the spares models for this thesis, research will be done to either validate or improve upon the current churn factor. Two churn studies were evaluated.

Mr. Bob Novak, a Operations Research Analyst from HQ AFLC/FMCA, performed the first of the analyses in 1987 using replenishment spares cost predictions obtained from the D041 computer system. The D041 product used in budget development is known as the Central Secondary Item Stratification (CSIS) report. Each June CSIS contains spare requirements forecasts for the June quarter and the following 12 quarters. As the fiscal year progresses, each passing quarter is dropped from the computations until the following June cycle when another fiscal year's (four quarters) forecast is added (LMMIM06, 1987:Ch 7, 8). As a result, the last quarter's requirements for each fiscal year will be predicted 12 times (once every quarter) over a three year period before the quarter is entered into. The assumption behind Mr. Novak's analysis was that the first time a quarter was predicted, it represented purely condemnations spares requirements. None of the changes associated with demand volatility would, he presumed, be

made until closer to the actual time that the quarter arrived. So by subtracting the first prediction for a fiscal quarter from the twelfth prediction for that same quarter, he assumed the delta would, in fact, be "demand volatility." He ran this analysis for several aircraft and received several different churn factors (i.e., last estimate divided by the first estimate). His bottom line recommendation was to support a 2.5 churn factor.

By his own admission, the number of aircraft studied and quarters of data evaluated were insufficient to justify conclusive findings. The Repairable Stock Program Manager pointed out that three of the five ALCs feeding quarterly inputs into the D041 system have failed to update the system during the June and December runs for as long as he could remember (Rosenthal, 1991). This also makes the results of the analysis suspect.

Mr. Ray Johnson, a Cost Analyst from the Air Force Cost Center, performed the second analysis, dated December 1988. He used weapon system obligation data from the Departmental On Line Accounting and Reporting System (DOLARS) tracking located at the Accounting and Finance Center, Lowry AFB, in Denver, Colorado and weapon system condemnations costs from the Weapon System Cost Retrieval System (WSCRS) located at Wright-Patterson AFB, Ohio in the analysis. In his study, Mr. Johnson compared the spares obligation data for twelve aircraft from FY 1979 to FY 1985 with the condemnations spares costs associated with these obligations. He dropped

three of the resulting ratios out of the analysis because he felt they were outliers and averaged the remaining nine values. His nine aircraft average was 2.15--the same value used today by HQ AFLC as the standard churn value for all LSC model computations. Mr. Johnson, like Mr. Novak, felt that his data set was too small to provide conclusive results (Johnson, 1991).

To perform a more comprehensive analysis of churn for this thesis, another approach will be used that combines aspects from both of the previous studies. An ideal data source would aggregate spares deliveries by weapon system for each fiscal year, so that actual deliveries could be compared to condemnations to develop a churn factor. The D041 system receives this sort of delivery data at the national stock number level but it doesn't have the capability to aggregate the information to the weapon system level (as needed for this thesis). Because of this, spares deliveries will be replaced by annual replenishment spares requirements generated by the D041 system (CSIS) and scrubbed by the Recoverable Stock Program Manager. These requirements will be compared to condemnations to develop a churn factor. This data is available in hard copy from the Recoverable Stock Program Manager at HQ AFLC/FMBSR. Condemnations data will come in hard copy format from the WSCRS system at HQ AFLC/FMCA.

<u>Independent Variable Selection</u>. Physical and performance characteristics of aircraft are available from a

number of sources (e.g. Air Force Guide No. 2, Vol. 1 (Green Book) and 2 (Brown Book), Rand, Jane's All the World's Aircraft). The Green Book and Brown Book contain official Air Force "blessed" data which is used by HQ AFLC/FMCA in their analyses and these sources will therefore be used (unless specified otherwise) in this analysis.

In an attempt to narrow down the candidates for independent variables, prior parametric models were evaluated to see which relationships were used and their supporting logic (see subsection entitled "Previous CER Work"). Additionally, a literature search was conducted for information pertinent to the independent variable(s) selection. The balance of this subsection provides the results of this analysis, beginning first with casual relationships which were *not included* in this thesis' CERs and then providing the logic behind those variables which were *included*.

Component reliability is logically related to recoverable spares requirements. Less reliable parts are more likely to fail and require more maintenance attention. If the failures themselves do not result in the parts being condemned, the increased maintenance activity may cause wear and tear on the component until it finally must be condemned. Engineering estimate based models such as the Logistics Support Cost (LSC) model use factors such as component mean time between demand (MTBD) to account for reliability. However, no equivalent reliability factor at

the weapon system level of aggregation was identified in the literature review..

A RAND study discussed several complications in determining recoverable spares requirements. Although engineering estimate based models typically include reliability factors such as the MTBD; because these factors are common to all users of the components, they lead one to assume (erroneously) that all users should expect the same levels of component reliability. However, the operating environments in which the components are placed vary considerably and this impacts the components' reliability. For example, summer temperatures at bases like Luke AFB are such that "temperatures in the avionics bay of idle aircraft may exceed the Mil Specs for solid state devices" (Crawford, 1988:10). At night the temperatures at Luke AFB cool down significantly, and the day to night differential is cited for causing leaks in hydraulic actuators (Crawford, 1988:10).

Changes in maintenance policies and training programs will impact the need for spare parts. Two TAC initiatives--Combat Oriented Supply Organization (COSO) and Combat Oriented Maintenance Organization (COMO)--encouraged "increased reliance on remove-and-replace actions instead of remove-repair-and-replace maintenance actions" (Crawford, 1988:10). Deployment of aircraft to Red Flag exercises may be accompanied by a surge in spares requirements as aging,

but still functioning parts, are replaced to ensure maximum performance during the training (Crawford, 1988:10).

Finally, the RAND study revealed that "to a certain extent demand patterns may follow parts availability" (Crawford, 1988:10). The number of aircraft continuing to fly with a certain defective, non-critical part may continue to rise until a shipment of the part becomes available--then a surge of requests for the part come in.

All of the complications identified in the RAND study have at least one thing in common. It is very difficult, if not impossible, to capture their effects in generic weapon system CERs. Even detailed engineering estimates do not adequately account for these factors. This accentuates the need for expert judgement in the requirements development process. "Good models" alone will not guarantee an accurate estimate.

The number of levels of maintenance (base, intermediate, and depot) can also be logically tied to recoverable spares requirements. In the initial spares arena, as the number of repair levels increases, so does the number of components in the repair "pipeline" required to achieve support objectives. Levels of maintenance can also be tied to replenishment spares due to the fact that pipeline requirements are typically paid for with replenishment spares funding when initial spares funds are inadequate. The levels of maintenance may also influence the design of the spares; which, in turn, may affect the

replenishment spares requirement. The relationship of maintenance levels to recoverable spares is more direct in the initial spares arena, and because an initial spares CER will not be developed in this thesis, no attempt was made to determine the number of levels of maintenance associated with each of the data base MDS.

The "bath tub curve" theory of reliability, as presented in AMGT 559, "Life Cycle Cost and Reliability," at the Air Force Institute of Technology (AFIT), was already mentioned in defining the scope of this thesis. This theory suggests that component failure rate (and therefore condemnations) is a function of component age--with failure rates that are higher during the early and late stages of a weapon system's life and relatively constant in between these extremes (Gill, 1991:21). The "inverse of average fleet age" is used in the ALERT spares model (Rexroad, Lucas and Collins, 1989:2) and the "average fleet age" is used in a RAND spares model (Crawford, Landsdowne, and Finnegan, 1988:22-23) to account for this relationship. However, given that the scope of this thesis has been limited to mature weapon systems (where, according to theory the failure rate is reasonably constant), this type of factor should have no impact on the recoverable spares requirements.

An unsuccessful attempt was made to evaluate the "inverse of average fleet age" factor as a check on the "mature weapon system" constraint placed on this thesis's

data base. The historical database for this variable (used in the ALERT model) was at the "MD" level of aggregation instead of "MDS." No other source for this variable was identified. If, when evaluated, the variable had been statistically significant, this would have been considered an indication that either: 1) immature or old weapon system data was erroneously included in the data (i.e., the separation of weapon systems as being early, mature, or old was done inaccurately), or 2) the bath tub theory is difficult to apply on real weapon systems that experience numerous modifications and therefore have components with a myriad number of different ages.

Not only is it logical to assume that components will deteriorate with age, it is also logical to assume that greater utilization of components will cause them to wear out due to repeated operational stress. One spares model accounted for this using annual "flying hours" as an independent variable (Crawford, Lansdowne, and Finnegan, 1988:24).

Unless one knows something about the intensity of these flying hours (i.e., the number of aircraft the hours are spread over), however, this measure does not logically seem to measure physical stress as much as it measures "opportunities for something to go wrong" (e.g., bird strikes). This doesn't invalidate "flying hours" as a potential cost driver. It simply changes its underlying logic. Its effect is similar in nature to a RAND spares CER

cost driver--the annual number of "active aircraft" in the MDS inventory (Hoffmayer, Finnegan, Jr., and Rogers, 1980:16). For this thesis, "annual flying hours", "number of aircraft" and "annual flying hours divided by the number aircraft" will all be evaluated.

For some components the "number of sorties per aircraft" or "landings per aircraft" would be a better indicator of physical stress than "flying hours per aircraft" (e.g., landing gear). The annual numbers of sorties and landings were obtained from AFALDP 800-4 (also referred to as AFALCP 800-4 and ALDP 800-4 in later versions), "Acquisition Management Aircraft Historical Reliability and Maintainability Data." The numbers of "sorties" and "landings" are, once again, considered measures of opportunities for things to go wrong. The "annual sorties per aircraft" and "annua landings per aircraft" are evaluated as measures of utilization intensity. "Annual flying hours divided by annual sorties" was evaluated as an indicator of MDS mission profiles. Greater sortie lengths should imply greater utilization of some components while shorter sortie lengths would imply greater utilization of others.

It should be noted that, due to holes in the annual sorties and annual landings data, those models developed with these variables or derivations of these variables had significantly smaller databases.

Some components are not being utilized during flight and others are utilized even before flight begins. However, given the weapon system level of aggregation in this thesis, it was not possible to account for individual component utilization differences.

Dummy variables will be used to separate the MDS by two classes of aircraft: 1) fighter/attack/trainer/fighter-bomber and 2) bomber/cargo/tanker. It is logical to assume that relatively light, highly maneuverable aircraft (fighter/ attack/trainer/fighter-bomber) put different kinds of stresses upon their components than heavy, unmaneuverable aircraft (bomber/cargo/tanker).

Engine spares account for a large percentage of the total recoverable spares requirement (Steinlagy, 1991) and therefore it is appropriate to evaluate independent variables which relate to this weapon system subsystem's requirements. "Thrust per engine" is cited as an indicator of engine complexity (Issacs, Montanaro, and Olivo, 1986:169). As this variable increases, one expects the number and cost of engine spares required to increase. For this thesis, maximum sea level static thrust is used. The "number of engines" per weapon system is related to the number of components which can be condemned and therefore to the spare requirement as well.

Another factor which contributes to the number of components is the weapon system size. Two types of sizing

factors will be evaluated for this thesis: 1) "empty weight" and 2) aircraft "length plus span."

Finally, weapon system technical complexity and performance are thought to influence the cost of annual spares requirements. Logically, one would expect high performance aircraft with high technical complexity to place greater stress on their components during operations. Additionally, the individual components are expected to be more expensive for the high performance, high technical complexity aircraft. Relating this logic to another transportation medium, one would expect a greater number of failures and more expensive failures on an Indy race car than on the family van.

In addition to the "thrust per engine" variable mentioned earlier, other candidate variables examined as performance and technical complexity drivers include: "maxload factor" (i.e., how many "Gs" was the aircraft designed to withstand), the "ratio of maximum takeoff weight to empty weight", the "maximum rate of climb at sea level," and the "maximum combat radius."

Data Population. The range of the aircraft "population" was largely determined by the availability of data meeting the "mature weapon system" criteria established in the thesis scope. The number of MDS included in the independent variable database was smaller for some of the variables. While most variables had five years of data for nineteen MDS (95 data points), "annual landings" data was

only available for sixteen MDS for varying numbers of years (41 data points).

Parametric Model Technique

As discussed before, part of the motivation for this thesis comes from the critical reviews being given to the current factor-based approaches used to develop spares estimates. This dissatisfaction was expressed in a SAF/FMC message, dated October 1990, and coordinated on by SAF/AQK, SAF/AQX and USAF/LEX (Robinson, 1991). The message stated their preference that demand based models be used during milestone reviews and for independent cost estimates. They questioned the use of factor based estimates when the data required for demand based models is usually available by Milestone II (program initiation approval).

The loss of insight into underlying causal relationships in the factor based method is not inherent in all parametric models, however. The problem lies in the fact that costs based on flyaway cost alone, although easy to use, do not include the driving forces behind the estimate. This thesis will attempt to develop a CER(s) with both increased visibility of its underlying causal relationships and the ease of use which is characteristic of parametric models.

Ease of use is an important consideration when analysts lack either the time or the expertise required to derive estimates from the more complicated demand based approaches.

It does no good to have a more powerful model if no one can use it.

Because the models are designed for use early in the acquisition life cycle, the aggregate level for the model will be at the weapon system level or perhaps at the major subsystem level. This is due to the limited data input available prior to completion of full scale development (TASC, 1989, Ch 5, 55). CERs are well suited for dealing with high aggregate level relationships.

Linear regression describes relationships between dependent and independent variables in mathematical terms and, therefore, is the logical choice for CER development.

Regression Assumptions

The following assumptions are required for the validity of classical regression analysis (Murphy, 1990-1991):

1) The appropriate cost drivers (independent variables) are included in the model.

2) The regression model specifies the correct relationship between the dependent and independent variables.

3) The independent and dependent variable data come from random distributions.

4) There is no bad data (i.e. free of measurement error, bias, and anomalies).

5) The regression error terms all come from a normal distribution with a mean of zero.

6) The error terms have constant variance and are independent from one another.

7) The cost drivers are independent from one another.

8) Predictions of future requirements can be made by examining past requirements.

The term "assumption" is a little misleading in that it implies that these properties are taken for granted. This is only the case when one is evaluating a poorly documented regression model. There are tests which can be performed to provide the analyst confidence that these "assumptions" are in fact true. The assumptions and the corresponding diagnostic tests will be discussed in more detail in the methodology section of the thesis.

Previous CER Work

Using CERs to predict spares costs is not a new idea. However, the fact that previous parametric models have been developed does not negate the need for new models. Because parametric models are based on historical data, they should be continuously revised and updated to reflect the most current available data. It is easier to validate an existing model with new data than to start from ground zero. A search was conducted, therefore, to identify existing spares parametric models. The following models will be discussed in this section: 1) Rand model, 2) Modular Life Cycle Cost Model (MLCCM), 3) Air Logistics Early Requirements Technique (ALERT) model, 4) Oversight of Resources and Capability for Logistics Effectiveness (ORACLE) model, and 5) Levine and Horowitz Study [The first three models meet the selection criteria for inclusion in Appendix C and are included there to make the appendix a

stand alone document. The discussion concerning the model's independent variable logic is more extensive in this section than in Appendix C because of its relevance to the selection of cost drivers for the CER(s) developed in this thesis. Appendix C also contains evaluations of non-parametric models]. A standard format will be followed as closely as possible for ease of comparison between the five models.

Model #1: Rand Model. All references in this subsection, unless identified otherwise, come from the developer's (see below) 1980 report, Estimating USAF Aircraft Recoverable Spares Investment.

Developer(s): K.J. Hoffmayer, F.W. Finnegan, Jr., and W.H. Rogers of the Rand Corporation, August 1980.

Model Purpose: The model is an update to a 1976 Rand model for estimating USAF aircraft recoverable spares investment. It includes models for estimating total replenishment spares requirements at the major subsystem level (airframe, avionics, and propulsion) and for estimating condemnation spares requirements at the same level (v). An attempt was made to develop an initial spares model but this was unsuccessful due to limited data availability (23). The models provide annual estimates for peacetime operating stock. War readiness material, spare engines, and engine spare parts are excluded. The models are intended for use prior to the preproduction or deployment decision stages of the acquisition life cycle (iii).

Model Algorithm: Table 1 provides a list of the independent variables associated with each subsystem CER.

Table 1

Subsystem CER Independent Variables (12-14)

Airframe CER	Avionics CER	Propulsion CER
Total active aircraft inventory of the given MDS	Total active aircraft inventory of the given MDS	Total number of installed engines in the MDS force
Airframe flyaway cost	Avionics flyaway cost	Propulsion flyaway cost
Peak flying hours per MDS per year	Dummy variable for bomber	
	Dummy variable for reconnaissance	
	Dummy variable for fighter/attack	
	Cargo dummy var.	
	Dummy variable for tanker	

The following logarithmic form is common to each of the subsystem CERs (11):

$$\log Y_{it} = \log \alpha + \sum_j \beta_j \log X_{ijt} + e_{it} \qquad (1)$$

where

Y_{it} = investment in POS spares inventory of aircraft subsystem i at time t.

X_{ijt} = the jth characteristic observed on aircraft subsystem i at time t.

α and β_j = regression coefficients.

e_{it} = the error for aircraft subsystem i at time t. The errors are assumed to be independent across subsystems but correlated over time with subsystem.

The source document states that a logarithmic form was chosen to develop the CERs due to their superior handling of heteroscedasticity and their more "real world" multiplicative nature (11, 15). They fail to clearly state whether the transformations are natural (ln) or common (log) logarithmic in nature.

Data Inputs and Sources: Cost data from 1975 to 1978 was provided for the following aircraft (7):

A-7D	C-5A	RF-4C	F-111D
B-52D	KC-135A	F-4D	F-111F
B-52G	C-141A	F-4E	T-37B
B-52H	F-4C	F-111A	T-38A

Specific data elements and sources are as follows (4-5):

D041 "Recoverable Consumption Item Requirements System:"

National Stock Number (NSN)
Unit Price (in then-year dollars)
Program Begin Date (earliest record of use)
Program Selection Code (Material Program managing part)
Organization Field Maintenance (OFM) Total Demand Rate (total item demand expressed in terms appropriate for its material program)
Base Level Condemnations (NSN level condemnations at base level)
Depot Level Condemnations (NSN level condemnations at depot level)
Total Overhaul Condemnations (NSN level condemnations resulting from planned overhauls)
Total Peacetime Operating Stock Assets
Application (the mission design series (MDS) or other stock number using the item)
Quantity Per Application

J041 "Procurement History File:"

National Stock Number (NSN)
Contract Date

Amount of Contract ($)
Quantity Procured

"Aerospace Vehicle Inventory Status and Utilization and Reporting System" (AVISURS):

Aircraft MDS
Calendar Year and Month
Flying Hours
Sorties
Landings
Average Number of Possessed Aircraft

Other data used in the model development was obtained from the following sources:

* TO 0025-30, Technical Manual, "Unit Cost of Aircraft, Guided Missiles, and Engines."
* USAF Statistical Digests
* PA, "USAF Program, Aerospace Vehicles and Flying Hours."

Assessment: The accuracy of the models provided are difficult to assess due to the minimal coverage of model diagnostics. Because Rand does not specify which base was used in the logarithmic transformations (natural or common), the reader is left to guess at the significance of the standard error of the estimate (the SEE is a measure of prediction accuracy for a transformation using the natural base)(Murphy, 1990-1991). The propulsion model CER has poor statistics: R^2 of .5841 and SEE of .67318.

It is unclear if the logarithmic form is really appropriate because they never actually state that they observed heteroscedasticity in the data; or why they feel a multiplicative equation is more "real world". They fail to document any diagnostics performed or other models attempted and discarded.

There was limited discussion concerning the logic underlying the independent variables chosen for the CERs.

The manner in which subsystem flyaway costs were included in each of the subsystem CERs may be questioned. One tenet of the integrated logistics support philosophy is that as an item's reliability improves, the reduction in its operations and support costs over its life cycle more than compensates for its increased acquisition cost (which has resulted from its improved reliability) (TASC, 1989:Ch 5, 25). The multiplicative nature of the subsystem CERs does not account for this belief logically. According to these CERs, increased acquisition costs will always result in greater spares costs.

Although the source text does not explain its rationale for using component flyaway costs, a case can be made that life cycle O&S costs reduce with improved reliability for reasons other than reduced spares requirements. After all, replenishment spares costs are only a subset of the total O&S costs. More reliable parts should fail less often and therefore cost less for maintenance and repair. If RAND believes that these types of savings exceed the increased spares costs associated with more expensive components, then their model logic is not contradictory to reliability theory.

In addition to airframe flyaway cost, the airframe CER included several additional cost drivers: 1) total active aircraft inventory of the MDS, 2) peak flying hours, and 3) mean organization field maintenance total demand rate. Total active aircraft inventory is a logical cost driver.

More spares are required as the number of aircraft increases.

Peak flying hours was used in lieu of programmed flying hours because it gave "a better statistical fit" (16). The authors stated that this resulted from "significant inventories of stock" remaining which had been purchased to support the Vietnam war (data is from 1975 to 1978) (16). Although this distinction was not clear to the author, the use of some sort of flying hour program is logical because one would expect that the more wear and tear that is placed on an aircraft, the greater the number of condemnations.

The mean organization field maintenance total demand rate (OFMTDR) was included as a "measure of airframe reliability" (17). Component reliability can be logically tied to condemnations because unreliable parts will fail more often and may, in the process, be damaged beyond repair or cause irreparable damage to other components. Additionally, even parts that can be easily repaired may receive wear and tear in the maintenance process itself (e.g., stripped bolts, etc) and therefore are condemned sooner than more reliable parts. In this model, however, the manner in which the OFMTDR was obtained is not consistent with application of the CER in early stages of aircraft development (where the authors claim their CERs are applicable). This variable was a "mean, weighted by the total item count, of the OFMTDRs of all the recoverable airframe items" (17). Since a complete list of airframe

items is unlikely to be available during early stages of aircraft development, it is unclear how this type of statistic will be readily available.

The Avionics CER included, in addition to avionics flyaway costs, dummy variables to distinguish the mission of the aircraft (bomber, reconnaissance, fighter/attack, cargo, or tanker) and, once again, the total number of active aircraft in the MDS inventory. It is logical that the amount of aircraft avionics equipment will vary by mission type, and the number of spares required should increase as the amount of avionics equipment increases. Total aircraft inventory is logical for the same reason explained previously.

The propulsion CER included only one additional cost driver besides the propulsion flyaway costs. The total number of installed engines in the MDS force is a logical cost driver--the number of spares required should increase as the number of engines increases. It should be noted that this CER includes no cost drivers which will vary over time. Engines spare parts account for the majority of the condemnation spares requirements (as seen in the dependent variable data set) and yet this CER would lead one to believe that propulsion spares remain relatively constant over time. This is in contradiction to the "bathtub" theory of reliability which states that failures (and logically therefore condemnations) are greater early in a weapon system's life due to manufacturing defects and later in life

due to wear out (Crawford, Lansdowne and Finnegan, 1988:23; Gill:21).

The RAND model was evaluated by an Initial Spares Working Group comprised of twenty two members representing HQ AFLC, ASD and HQ AFSC. They concluded that the model's database should be updated and a clear distinction made between initial and replenishment spares before they could use the model (Rexroad and others, 1990:11).

Model #2: Modular Life Cycle Cost Model (MLCCM). All references in this subsection, unless specified otherwise, come from Grumman Aerospace Corporation's 1986 report entitled Modular Life Cycle Cost Model for Advanced Aircraft Systems, Cost Methodology Development and Application. The authors were R. Isaacs, N. Montanaro, and F. Olivo.

Developer(s): Grumman Corporation, Program Team directed by Mr. R. Isaacs, September 1986.

Model Purpose: The MLCCM is a parametric-based series of models for

> predicting advanced technology aircraft costs, to the major subsystem levels, for the Research, Development, Test, and Evaluation, Production, Initial Support, and Operations and Support phases of the system life cycle during conceptual and preliminary design. (Isaacs, 1986:iii)

Initial and replenishment spares are but subsets of the overall costs within the production and O&S periods, respectively. Their cost is broken out for 14 subsystems (structure, crew system, landing gear, flight control, cargo

handling, engines, engine installation, environmental control systems, electrical, hydraulic/pneumatic, fuel system, avionics, armament, auxiliary power unit) (11) for two classes of aircraft (fighter/attack/bomber and cargo/transport/tanker)(x).

Model Algorithm: Because the MLCCM was developed as a tool for conducting trade studies during the design stage, the CERs were developed using a Work Breakdown Structure (WBS) format. In this way the design engineers would be able to relate costs to the WBS elements for which they were responsible. Step-wise regression was used to develop log-linear regression equations. Again, it is unclear if they used natural or common base transformations. They limited, for most cases, the number of parameters in any CER to one third the number of data points (47-48). While it makes sense to preserve degrees of freedom by limiting the number of variables used (compared to the number of data points), it isn't clear why the developers' chose one third as a criteria ratio.

Data Inputs and Sources: Cost data was derived from several sources including: "Visibility and Management of Operating Support Costs" (VAMOSC) system, AFR 173-13 Factors, and the 1975/1976 Operating and Support Cost Estimating Report. Independent variable technical data sources include: Standard Aircraft Characteristics (SAC) charts, group weight statements, technical orders, and the manufacturer.

> The SAC charts were used to obtain data on engine design and performance, fuel and tankage, armament, loading and aircraft performance, development dates, etc. Weights, areas, volumes, dimensions, and general aircraft design characteristics were obtained from the group weight statements and the manufacturers. Flight manuals were used for data on electrical, fluid power, and flight actuator systems and for general aircraft design characteristics as well [note that not all of these variables are used in the replenishment spares CERs]. (13)

<u>Assessment</u>: The fact that the models were developed with obligation data brings with it all the uncertainty previously discussed in the data problem section. The report admits the need for better cost data inputs (219).

The model statistics provided were not complete. "R" values were provided as opposed to the "R^2" statistic commonly seen. The R^2 values for 5 of the 14 subsystems in the fighter/attack/bomber class of aircraft were poor (less than .7) (165-169). No discussion of model diagnostics was provided.

The independent variables used in the subsystem CERs differ between two general classes--those for cargo/transport/tanker aircraft and those for fighter/attack/bomber aircraft. The following text describes the independent variables used in the cargo/transport/tanker class and how the variables logically impact subsystem spares requirements:

1) Structure CER: "Cargo weight" and "cargo volume" were included as measurements of aircraft size.

"The size of the aircraft directly relates to the amount of structural spares required" (209).

2) Crew Systems CER: The "number of primary compartments" and the "length + span" (LENSPN) were included as measures of the fuselage interior. "As such [they] reflect a degree of the demands imposed on the crew system. Increased size results in larger crews, seats, etc, and as such results in an increase in replenishment spares costs" (209). Apparently the logic here is that larger crews require bigger "crew systems," composed of more parts, and therefore more spare parts are needed.

3) Landing Gear CER: The "number of landing gear wheels" is included as "indicative of the number of wheels, tires, brakes, and associated hardware requiring repair action and maintenance attention" (210). "An increase in the number of wheels results in an increase in [subsystem] replenishment spares costs" (210).

Additionally, the "Mass times Velocity Squared" (MVSQ) is included as a measure of the energy absorption requirement placed on the landing gear. "An increase in the MVSQ results in abuse to the wheels, tires and brakes. Consequently, an increase in replenishment spares costs will result" (210).

4) Flight Controls CER: The "number of flight control actuators" (NOACTS) is included as "an indicator of the overall complexity of the flight control subsystem . . . [and] one of the largest contributors to the cost of spares"

(210). This increased complexity is said to cause "increased removal activity of the major flight control components" and thus an increased spares requirement (210). It isn't clear if this means complex systems have a greater number of parts which can fail or if it takes more work to remove the components causing more wear and tear that is maintenance related.

The "takeoff gross weight maximum" (TGWMAX) is included as "a measurement of aircraft size and, as such, is an indicator of flight control size. The larger aircraft requires more flight control components and, as such, more spares" (210).

5) Engine Installation CER: Again, TGWMAX is included as a measure of aircraft size. Size is said to be proportional to spares cost. The "engine pressure ratio is a measure of engine sophistication and, as such, has an influence on the engine installation component requirements" (211) [The source text describing the subsystem CERs and their supporting logic did not specify what type of "engine pressure ratio" is used]. An increase in the number of installation components means that more parts are available to fail and therefore more spares should be required.

6) Environmental control System (ECS) CER: "Hours per mission" is included as a measure of aircraft and component usage. "Maintenance cost increases with aircraft utilization" (211).

"Fuselage Volume" (FLGVOL) is said to measure the "ECS size and complexity relative to the amount of cooling capacity" (211). As this variable increases, so does the size and number of ECS components resulting in increased spares requirements.

7) Electrical CER: The "number of generators" is included as a measure of the "size and number of components in the electrical generating and distribution system" (212) Again increased size equates to increased spares requirements.

The "cargo floor area" is a measure of the space requiring electricity. "An increase in the useable floor space results in an increase in size of the electrical subsystem and consequently replenishment spares costs" (212).

8) Hydraulic/Pneumatic CER: The LENSPN and "number of hydraulic pumps" are included as "measures of the size and complexity of the aircraft hydraulic system and indicative of the number of supply circuits and components required" (212). Again, as size and complexity grows the spare requirement is also said to grow.

9) Fuel System CER: The LENSPN and "fuel system weight" are included as "measures of aircraft size, and hence, fuel system size" (213). Increased size relates to increased spares requirements.

10) Cargo Handling CER: "Cargo weight" and "cargo volume" (CARVOL) are included as measures of the cargo

handling subsystem's load capacity. As the number and size of cargo handling equipment increases, so does the number of spares required.

11) Auxiliary Power Unit CER: FLGVOL and CARVOL "are sizing factors relative to the amount of air conditioning to be supplied by the APU" (213). As these variable increase, "larger and more complex" APUs must be used and thus, an increased requirement for spares (213).

12) Avionics CER: "Total KVA" and "avionics black box weight" were included as measures of the avionics subsystem size and complexity. Increases in these variables are said to result in increased spares costs.

13) Engine CER: "Sea level maximum mach" and "thrust per engine" were considered measures of engine complexity. "The more complex the engine, the more costly are the spares, therefore, an increase in these parameters will result in an increase in the cost of spares" (169). This CER was also used for the fighter/attack/bomber class of aircraft's engine CER.

Rather than detailing each subsystem's independent variables for this second class of aircraft, the following text describes only those cost drivers which weren't already mentioned above.

The landing gear CER for this class included "takeoff gross weight clean" as a cost driver. This was said to be a measure of the "kinetic energy absorption capability and size of the landing gear components," and because of this,

it directly related to tire, brake and wheel wear, and thus the need for more spares.

The engine installation CER included "engine thrust to weight ratio" as "a degree of sophistication and size [of what the documentation does not say] in relation to the aircraft performance capabilities" (166). Increases in these factors are said to lead to increased maintenance activity and thus, the need for more spares.

The environmental control system CER includes "BTU per hour" as a "measure of the cooling capacity and the size of the ECS" (167). Increased size, once again, equates to a need for more spares.

"Avionics installation weight" is used in both the electrical CER and the Avionics/Armament CER. This weight is said to be a measure of the size and number of components in the avionics subsystem. An increase in this variable leads to increased spares requirements for both subsystems.

The fuel system CER uses "internal fuel weight" as a measure of the size and number of fuel system components. The greater the number of parts, the greater the number of spares required. Additionally, "maximum mach" is used as "a degree of sophistication required of the fuel system" (168). Increased sophistication is said to require more parts and thus more spares.

The discussion of independent variable selection contained in this model's documentation needs additional work. In many cases it isn't clear why one measure of size

is used in one CER and another size measure is more appropriate for another CER. It some cases it appears as though the authors had to stretch their imagination to come up with the logic behind their cost drivers. This might be attributable to the fact that step-wise regression was used to identify the cost drivers. The logic might have been developed after the selection of cost drivers.

Model #3: Air Logistics Early Requirements Technique (ALERT). Unless stated otherwise, references in this subsection will come from a 1989 report entitled Air Logistics Early Requirements Technique (ALERT) FY90-94 Program Objective Memorandum (POM) Forecast. The authors were Adrienne Rexroad, Robert Lucas, and Larry Collins.

Developer(s): AFLC/MMM, 1984.

Model Purpose: ALERT has been used since 1984 by HQ AFLC as the starting point for developing BP15 aircraft peacetime spares Program Objective Memorandum (POM) inputs. The POM is the Air Force's long range budget requirements document. ALERT is the "starting point" because the output from ALERT is scrubbed by the BP15 Program Manager prior to its submittal (1).

Model Algorithm: Sixteen separate CERs are developed with straight linear regression to predict the first year of POM requirements for thirteen different weapon systems, the F-100 engine, common spares (to multiple weapon systems), and an "other" category. This first year's estimate is then used as historical input for the next four

years' predictions--a regression technique which is referred to as "bootstrapping." (2).

<u>Data Inputs and Sources</u>: The dependent variable data used were the requirements submitted in the last Budget Estimate Submission (BES). There were a total of four independent variables used (not all at once) in the CERs: 1) Mission Design Series buy requirements from the D041 "Recoverable Consumption Item Requirements System," 2) Average Fleet Value, as calculated by USAF/AC, 3) the reciprocal of the estimated Present Fleet Age, also provided by USAF/AC, and 4) Chronological Year.

<u>Assessment</u>: Only six of the sixteen weapon system class CERs had adjusted R^2 values exceeding .7 and only one class exceeded .75. The BP Manager scrub that followed subsequent to the ALERT run changed the input values further. The BP Manager is critical of the D041 input data since it uses the June data run (a quarter not updated by three of the five ALCs). He also questioned the logic of using the fleet value as a cost driver. USAF/AC based their estimate of fleet value on projected future flying hour programs which decrease over time. The fleet values, therefore, decrease over time. The spares requirement, however, logically gets larger as the fleet gets older (7).

A 1988 validation study of the ALERT model compared the scrubbed ALERT forecast to three other forecasting approaches: 1) cost per flying hour factors, 2) inflation growth, and 3) unscrubbed, "pure" ALERT forecasts. This

analysts concluded that the scrubbed ALERT forecast was the most accurate approach and, in fact, this technique predicted (in 1984) 1987 spares requirements within two percent of the actual obligations recorded that year (Rexroad and Collins, 1988:8). However, it should be noted that this "two percent" accuracy was for the total replenishment spares forecast. Within the individual CERs, several of the estimates missed the mark considerably. The B-52 estimate ($148.2 million) was $109.2 million higher than the funds obligated. The F-16 estimate ($372.2 million) was $225.6 million higher than actuals and the F-100 engine estimate ($393.4 million) was $232.4 million lower than the actual obligations (Rexroad and Collins, 1988:7-8). The remarkable "accuracy" of this model, therefore, could be nothing more than the Air Force obligating everything they had to obligate (provided as a result of the ALERT forecast), without saying anything about whether real requirements were met.

The validation study pointed out several concerns with the model. A chi-square test was performed on all four estimating techniques being evaluated and it was determined that "none of the forecasting approaches are statistically close to the actual obligated dollars" (Rexroad and Collins, 1988:9). Additionally, the authors concluded that although a high correlation existed between the dependent variable and the independent variables in their data set, they found no causality and therefore had no "complete 'intuitive'

interpretation of why past relationships exist" (Rexroad and Collins, 1988:5). The authors recommended that additional analysis be performed to "include variables like actual flying hours, type of mission, and the expected occurrence of a major modification to predict cause and effect relationships" (Rexroad and Collins, 1988:10).

A 1988 RAND report (see next model below) provided a brief evaluation of the ALERT methodology. One additional shortcoming which it identified is that the model does not "correct for inflation by converting dollar estimates into constant dollars" (Crawford, Lansdowne, and Finnegan, 1988:8).

Model #4: Oversight of Resources and Capability for Logistics Effectiveness (ORACLE). Unless stated otherwise, all references in this subsection come from a 1988 RAND report entitled, ORACLE and Requirements Forecasting, Vol. II: Predicting the Peacetime Spares Requirement. The authors are Gordon B. Crawford, Z.F. Lansdowne, and F.W. Finnegan.

Developer(s): RAND Corporation (see authors above).

Model Purpose: ORACLE is "a methodology developed to relate dollars expended on recoverable components to the goals set in the Planning, Programming, and Budgeting (PPB) process" (1). The ORACLE methodology was developed with three hypotheses in mind:

1. A constant requirement methodology and the converting of prices to constant year dollars with reasonable inflation indices would make the BP15 requirement more stable and more readily predictable.

2. Breaking the total requirement for a weapon system into several federal stock class (FSC) groupings and analyzing the regression of each group on the several explanatory variables would permit identification of certain groups that do not regress well and hence deserve expert attention and judgement to predict their requirement.

3. Removing these 'hard to predict' groupings for individual attention would then make the remainder of the expenditure substantially more stable and easier to predict. (2)

Model Algorithm: CERs were developed for three weapon systems (F-15, F-16, and C-5). Ten years of data (1975 - 1984) was used for the C-5. In the case of the F-15 and F-16, the data bases were reduced to seven years (1978 - 1984) and six years (1979 -1984) respectively. The modelers felt that these aircraft were too new to the inventory in the mid-70s and that this early data would not accurately predict the requirements for mature weapon systems.

The modelers performed what they called "a loose approximation of what others might call a regression analysis" (19). They say this because they did not believe that the residuals in their analysis would be "normally distributed with a precisely described covariance matrix" (19) [see regression assumptions 5 and 6 on page 20] and they took "repeated and excessive liberties" in such subjective areas as "rejecting outliers and replacing their

values" (22). The modelers claim that if the CERs did not perform well under these relaxed conditions, they would perform even poorer using the stricter linear regression assumptions (20).

The dependent variable being studied for each weapon system was the marginal annual cost of the replenishment spares requirement. Given the small size of the F-16 data base, the authors limited the number of coefficients in any one CER to two (assumably to preserve degrees of freedom). The independent variables evaluated included the average age of the fleet, flying hours and the value of the fleet. Little explanation is given for why "value of the fleet" is used other than the Navy has "long used it to predict Naval air requirements" (22). The "average age of the fleet" is included to account for the "bath tub" theory of reliability (described earlier in the RAND Model evaluation) (23). The "Flying hours" variable was included to account for the fact that "many spare parts fail as a result of repeated physical stress or wear that is a direct result of flying, taking off, or landing" (24). "Flying hours" were used in lieu of "aircraft sorties" due to better availability of flying hour data and the modelers' contention that, when plotted, a curve describing sorties per year "tends to look like curves that describe flying hours per year" (24).

As stated earlier, the modelers wanted to determine if, by separating hard to predict FSC groupings, they could improve their ability to predict requirements for the

balance of the weapon system's requirements. In other words, they wanted to separate the "art" (hard to predict groupings requiring expert judgement) from the "science" (remaining groupings) in spares requirements determination (25). To accomplish this, separate CERs were developed for fourteen separate FSC classes for each weapon system, in addition to the overall weapon system CER. Those FSC classes which failed to show a strong statistical relationship to the independent variables were then removed from the overall weapon system data base and the impact on its CER was noted.

<u>Data Inputs and Sources</u>: The dependent and independent variable data used in this analysis (discussed above) was taken from the D041, "Recoverable Consumption Item Requirements System."

<u>Assessment</u>: The idea of separating "hard to predict" components from the total weapon system data base is an interesting and logical idea. According to the modelers' conclusions, they did find support for their second hypothesis that this sort of separation could be accomplished. Some of the FSC groupings exhibited "wild swings," and the modelers felt that they would be difficult to predict no matter what independent variables were used (41). Unfortunately, the exclusion of these FSC groupings, according the modelers, showed no marked improvement in the ability to predict requirements for the remainder of the FSC groupings. The first hypothesis (concerning anticipated

improvements garnered from a constant requirements methodology and constant year dollars) was also not supported. Additional research would have to be conducted to determine if a larger data base or different independent variables would impact these results.

Model #5: Levine and Horowitz Study. Unless stated otherwise, references in this subsection will come from a 1989 study conducted by Daniel B. Levine and Stanley A. Horowitz ent tled, Predicting the Cost of Initial Spares.

Model Purpose: The purpose of this study was to develop a CER for predicting initial spares costs. The CER would benefit service and OSD budget planners in laying in long range budgets for new aircraft many years before their deployment (1).

Model Algorithm: The authors used linear regression to test hypothesized relationships in data from twenty one Navy and Air Force aircraft. The dependent variable was the total obligation authority (TOA) for procurement of initial spares during the life of the weapon systems' programs. Actual obligation data is used from 1972 - 1988, and TOA is included through 1994. Aircraft mission design series (MDS) selected were limited to those MDS for which data was available for the entire program (i.e., the program started after 1972 and will finish before 1994). Independent variables evaluated included weapon system cost, empty weight, maximum speed, total program procurement

quantity, and dummy variables to control for the aircraft mission (2).

Three criteria were established for selection of the final CER(s): 1) positive signs for the cost driver coefficients, 2) high R^2, and 3) high t-statistics (2). This study resulted in the development of four CERs which met the criteria.

Data Inputs and Sources: The dependent variable data came from the FY 1989 historical procurement annex covering the fiscal years 1972 - 1994. The independent variable data (discussed above) came from "Standard Aircraft Missile Characteristics" (Air Force Guide No. 2) and *Jane's All The World's Aircraft* (5).

Assessment: The use of actual obligations as the dependent variable carries with it all the uncertainties discussed previously in the subsection entitled "data problems" (e.g., "what was spent" is a proxy for "what should have been spent," some initial spares requirements were purchased with replenishment spares budget authority, etc.).

The authors provided no discussion of the logic behind the cost drivers selected other than to say they anticipated a positive relationship with the dependent variable. The two CERs with the highest R^2 values both involved the single independent variable, "weapon system cost." One CER was linear and the other involved a logarithmic transformation of the dependent and independent variable. The authors made

no comment as to which CER they felt most accurately described the true relationship. This, they said, depended upon "the analyst's best intuition about the underlying relationships" (8). The next model included three linear independent variables--procurement quantity, empty weight, and maximum speed. The final model included these same variables plus two dummy variables to distinguish attack, fighter, electronic, and bomber aircraft from cargo and tanker aircraft (8). Again, there is no discussion concerning which relationship the authors preferred, and no discussion of any model diagnostics performed at any time during the study.

Literature Review Summary

Throughout the course of the literature review, one factor stood out--and that was the great number of difficulties associated with developing spares CERs. Upon concluding their attempts to develop a better spares CER, RAND modelers summarized their feelings: "In short, the problem is extremely difficult. That was clear before, but it is even clearer now" (Crawford, Lansdowne, and Finnegan, 1988:vi). Data selection poses numerous problems for model developers. Assuming one can even locate a data source, one is often disappointed to find that: 1) the data is at the wrong level of aggregation, 2) the data covers a different time span than required (e.g., calendar year instead of fiscal year), 3) there are strategic holes in the data, and

4) the data is discredited by numerous other factors (e.g., the obligation data is influenced by political considerations, is hard to track to spares usage due to its multi-year availability, etc.).

An examination of existing spares CER based models provided ideas for cost driver candidates but little comfort that a statistically significant model would be found. The models were weak in this area (i.e., poor R^2's, poor mean standard errors, etc.). The model source documents were also weak in explaining the underlying logic behind their models. One had no idea, for the most part, if the relationships found were correlational or causal in nature. Additionally, the model source documents provided little, if anything, in the way of model diagnostics descriptions.

Although the author cannot guarantee that he will develop a statistically significant model, an attempt will be made to improve upon (relative to the models evaluated in the literature review) the documentation of the model.

III. Methodology

Introduction

The general overview of the entire cost estimating process (research objective number one) and summary-level description of current O&S cost models applicable to spares (research objective number two) are purely descriptive in nature. This chapter will explain the methodology used in support of research objective number three.

This third objective involved developing a parametric model for predicting recoverable spares costs. No initial spares CER was attempted due to a lack of practically accessible data, as identified in Chapter II. The replenishment spares model was accomplished in two parts: 1) a multiple independent variable (MIV) CER relating condemnation costs to aircraft physical and performance characteristics, and 2) a single independent variable (SIV) CER comparing replenishment spares requirements to condemnation costs. This second part is, in essence, part of an attempt to develop a demand volatility factor. The predicted condemnation spares cost must be multiplied by its associated demand volatility factor to arrive at the total replenishment spares estimate. Both MIV and SIV models were developed with linear regression using SAS statistical analysis software (maintained on the Air Force Institute of Technology (AFIT) VAX computer system). The data used to develop the condemnations CER is at the "MDS" level of

aggregation; while the demand volatility factor data is at the "MD" level. This chapter provides a detailed explanation of the methodology used to create both models, beginning first with the condemnations CER and ending with the demand volatility CER.

Condemnations CER Development

The following subsections discuss the specific procedures which were used to develop and validate the condemnations spares model. General explanations are given for some terms and the reason for using techniques are explained, but detailed explanations of the actual regression techniques are not. Readers who are unfamiliar with linear regression will need to refer to a regression text for further details. The techniques mentioned below are from the COST 671 (Defense Cost Modeling) and COST 672 (Model Diagnostics) courses taught at AFIT (Murphy, 1990-1991).

Model Identification. The first step in developing the condemnations CER involved identifying logical cost drivers. This process is known as model identification. In order to identify the underlying causal relationships which drive a cost estimate, one should become familiar with the system(s) for which the cost estimate is being developed. Given the time constraints of this thesis, this task was accomplished through a review of previous spares CER work and consultation with spares experts. While one can never be

sure of capturing all the cost drivers, statistical measures (which will be discussed shortly) can be used to determine what portion of the total error is captured by the model.

A specific consideration under the general "model identification" heading is testing for interaction effects and indicator variables. Both were examined in the model development. If one changes the value of an independent variable and the resulting change in cost is dependent upon the value of another independent variable, there is an "interaction effect" between the independent variables. For example, if the change in spares cost related to a change in an aircraft's "maximum speed" also depends upon the "empty weight" of the aircraft, there is interaction between these two variables. "Maximum speed" and "empty weight" were in fact tested for an interaction effect, along with "maximum load factor" and "aircraft length plus span." This was done by multiplying the variables against one another in each of the above pairs. The resultant products became new candidate independent variables.

Indicator variables are used to determine if the sample population can be divided into separate classes based upon qualitative differences. Indicator variables were included to determine if spares costs are related to the following categories of aircraft: 1) fighter, attack, fighter-bomber, or trainer aircraft; or 2) bomber, tanker and military transport.

Model Specification. Closely related to identifying the cost drivers is the next step--hypothesizing logical relationships between the dependent variable (cost) and the independent variables (cost drivers). This process is known as model specification. For example, "is the relationship linear or non-linear?"

There is no simple way to quickly develop a CER from a list of cost driver candidates. Knowing which variables to include in the model and what relationships to specify requires a great deal of professional judgement. One should ensure that a model makes logical sense. For example, a model may use aircraft weight as a cost driver for recoverable spares. The logic behind this driver could be that increased weight implies more aircraft parts and therefore more spares are required. However, the aircraft for which spares costs are being predicted may be heavy because it is built with heavier, sturdier materials. In this case, the model logic fails because the heavy aircraft weight is not due to more parts. Rote application of a CER, without professional judgement, can lead to erroneous estimates.

When numerous variables are identified as potential cost drivers, one must do one's best to determine which variable or set of variables constitute the most logical CER. The more candidates for inclusion there are, the greater the number of possible combinations that one is tempted to evaluate. The danger here lies in the fact that

simply by testing a large number of different candidate variables using different assorted transformations, it is likely that one can develop a statistically significant model merely by chance. Additionally, with no logical expectations concerning the underlying causalities of the variables, one has no basis for determining if a statistically significant model is based upon correlation between the dependent and independent variables, as opposed to causality.

Given the pitfalls associated with arbitrarily testing different combinations of variables, the author attempted to identify expected relationships prior to running the models themselves. It seemed logical that sizing variables such as aircraft "empty weight" and "length plus span" and the annual utilization factors, "flying hours," "sorties," "landings," and "number of active aircraft in MDS inventory," would have direct linear relationships to condemnation costs. No plausible rationale could be thought of for either an inverse relationship or even a direct relationship with a changing slope.

For "intensity" of utilization factors such as "flying hours per aircraft," "landings per aircraft," and "sorties per aircraft," and performance/technical complexity factors such as "thrust per engine," "maximum speed," "maximum climb rate at sea level," "maximum load factor," etc., it was felt that condemnations costs would increase at an increasing rate as these factors increased. This type of relationship

is typically tested with quadratic transformations and/or logarithmic transformations of both the dependent and independent variables ("log-log" transformations).

The "flying hours per sortie" factor (mission profile factor) was thought to cause condemnation costs to increase but at a decreasing rate. Given that an aircraft is performing the same type of mission continuously, performing it for longer periods of time will result in increased wear and tear on the aircraft. However, after a point, longer missions begin to reflect different types of missions. A long ferry mission may not cause as much wear and tear as a shorter mission practicing "touch and go's." This type of relationship is typically modeled by raising the independent variable to the ".5" or "-1" power, a log-log transformation, or a logarithmic transformation of the cost driver alone.

The aircraft "flyaway costs" is expected to have a direct relationship to condemnations costs. More expensive aircraft means more expensive parts and it is felt that this will outweigh any reduction in condemnations due to improved reliability (which may drive the higher acquisition cost). There was insufficient evidence to judge whether this should be a linear relationship or not.

<u>Data Normalization</u>. Once the hypotheses to be tested were developed, the raw data was collected and then normalized. This was required to ensure that differences in costs between different years was not merely related to

inflation effects. The dependent variable data obtained from the Weapon System Cost Retrieval System (WSCRS) was already inflated to a common base year--FY91. The replenishment spares annual requirements used in the demand volatility analysis had to be inflated to FY91 dollars also.

Linear Regression. The next step involved actually using SAS to specify the relationship between the dependent and independent variables in mathematical terms. SAS fits data to a regression line using the method of least squares best fit.

Each regression line is expressed in the following equation form:

$$Y_i = B_0 + B_1X_{i1} + B_2X_{i2} + \ldots + B_{p-1}X_{i,p-1} + \varepsilon_i \qquad (2)$$

(Neter, Wasserman, and Kutner, 1989:229)

where

$B_0, B_1, \ldots, B_{p-1}$ are parameters $X_{i1}, X_{i2}, \ldots, X_{i,p-1}$ are known constants

ε_i are independent $N(0, \sigma^2)$ $i = 1, \ldots, n$

SAS can only work with linear relationships and so cost drivers with anticipated non-linear relationships were transformed (e.g., setting the independent variable equal to itself raised to a power) so that the relationship would be linear as transformed.

The initial SAS runs were made using selected logical linear independent variables. Additional runs were then

performed based upon what logically made the most sense and the results of this initial analysis.

The SAS forward stepwise regression function evaluates how the model statistics change as SAS adds each possible independent variable one at a time to the model, starting with the most significant variable. This function does not guarantee the best model, however, and it was used only as a check against the final model developed.

<u>Model Validation</u>. Having stated that developing a CER is not an easy task, it is appropriate to discuss the diagnostics which can be performed to check a model's internal validity. Each SAS regression run provides an analysis of variance (ANOVA) table with many of the statistics necessary to evaluate the model (e.g., R^2, Adjusted R^2, F-Value, etc.). The format of this table is provided in Table 2.

Numerous factors must be evaluated before a final CER is selected. One simple check is to examine the signs of the parameter estimates from each ANOVA table to see if they are logical. For example, a negative sign would be logical if one had reason to believe that the relationship between the cost driver and cost was inverse.

Given a logical sign for the parameter estimate, a number of statistics from the ANOVA table can then be examined together to determine the overall predictive strength of the model. The coefficient of determination (R^2) tells one the percentage of total squared error

TABLE 2

ANOVA Table Format (SAS)

Source of Error	Degrees of Freedom	Sum of Squared Error	Mean Squared Error	F Value	P Value
Model	P-1	SSR= $\sum(\hat{Y}_i-\bar{Y})^2$	MSR=SSR/df	MSR/MSE	*
Error	n-P	SSE= $\sum(Y_i-\hat{Y}_i)^2$	MSE=SSE/df		
Total	n-1	SST= $\sum(Y_i-\bar{Y})^2$	MST=SST/df		

Root MSE	*	R-squared	*
Dep Mean	*	Adj R-sq	*
C.V.	*		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for HO: Parameter=0	Prob>¦T¦
Intercept	*	*	*	*	*
Driver#1	*	*	*	*	*
Driver#2	*	*	*	*	*
Driver#P	*	*	*	*	*

Where

$\hat{Y}_i$ = the ith fitted value on the regression line

$\bar{Y}$ = the mean of the observed values in sample set

Y_i = the ith observation from the sample set

P = the number of parameters in the model

n = the number of observations in the sample set

accounted for by the regression line. For this thesis, the general rule of thumb is that one doesn't want to accept an

R^2 value less than 70%. A value of 80% or greater was looked for in the final model. This statistic can be misleading, however, in that it can be artificially driven up by increasing the number of independent variables whether they are true cost drivers or not. For this reason the adjusted R^2 was compared to the R^2 value. If the two values were not within 20% of one another, it was assumed that insignificant variables were impacting the R^2.

The F-test was used to check the statistical significance of each overall model evaluated and the t-test was used to check on each individual independent variable's significance given that the other independent variables were included in the model being tested. The probability values associated with the F and t-values were used to determine at what level of confidence the variables could be considered significant. Again, 70% is a typical rule-of-thumb minimum. An 80% or better value was sought in the final model.

The P-Value was looked at to determine "the smallest significance level at which the null hypothesis can be rejected" (Newbold, 1988:339). Since one wants to reject the null hypothesis (because one believes a relationship exists to begin with), obviously the smaller the P Value the better.

The coefficient of variation (CV) and prediction intervals (SAS has functions that can print out the 95% prediction limit bounds and, for SIV models, plot these bounds around the regression line) were used to examine the

model's external validity. The CV provides approximately a 70% prediction interval (estimate plus or minus CV) at the center of the data. If a natural logarithmic transformation of the dependent variable was used, the CV was replaced by the root mean squared error (MSE) (which equates to the CV in a natural logarithmic transformation). Since the CV (or root MSE) gives one a rough idea of how well one is predicting at the center of the data, where the bounds are the smallest, a large CV can end the analysis because one knows that it's not going to get any better. If the CV is small, however, the prediction interval analysis can be used to examine how well the model predicts over the entire sample data set. The larger the prediction intervals, the more uncomfortable one becomes over the model's predictive capability. If the prediction intervals seem to widen dramatically at the outer edges of the sample data, this will be taken as an indication that the model may only apply to the range of the current data set.

In order to identify which data points are in the center of the data and which are at the outer edges, one can examine the width of the prediction limit bounds for each data point. Those data points with the smallest prediction intervals should be relatively close to the center of the data, while those with the largest prediction intervals should be the farthest from the center of the data. When conducting this analysis on a model with a log-log

transformation, one should examine the prediction intervals in logarithmic space as opposed to arithmetic space.

In addition to the 95% prediction intervals provided by SAS, 70%, 80% and 90% prediction intervals will also be derived (for the data point closest to the center of the data) to determine the impact of changing confidence levels upon the model prediction intervals. These bounds will be plotted around the predicted value to graphically depict how the bounds increase as the alpha level decreases.

None of the statistics described above, taken alone, can tell you how "good" the model is. They all must be considered together to evaluate the various models because, for example, R^2 can be artificially inflated at the expense of the model's significance. Additionally, these statistics are only meaningful if one can assume that the model is properly identified and specified. The diagnostics, therefore, do not stop with these statistics.

Residual Plots. Another check is to see if the models are properly specified. SAS allows one to plot the residuals (deltas between the observed and predicted condemnation costs) against the independent variable data. Theoretically, one can examine these plots for patterns in the data and if all the residual plots appear to be completely random, then one may assume that the model is properly specified and no further action is required. If even one plot shows a pattern, this indicates that the data is not linear as transformed and thus a (different)

transformation is required. If and when this is the case, two other SAS functions can be used in combination with these basic residual plots to determine which transformations are required. Partial regression plots and residuals plotted against important independent variables omitted from the model can also be used to identify necessary transformations. This "theoretical" procedure was not followed in this thesis, however, because patterns in the data were expected but not found. Rather than stopping at this point, the author went with his professional judgement and continued with the partial regression plots and omitted variable plots, hoping to identify necessary transformations. Each time a variable was transformed, the process was started all over with plotting the residuals for every independent variable and checking for patterns in the data. Additionally, transformations which made logical sense were evaluated, even in the residual plots did not indicate that the transformations were necessary.

Outliers. Still another check involves identifying outliers in the sample data. SAS has a function which prints out leverage values (measurements of an observation's distance from the center of the data) which can be used to identify outliers with respect to X. If a leverage value (h_{ii}) is greater than twice the number of parameters (P) divided by the number of data points (n), than the data point is an outlier. If P is large relative to n, then this formula's value may exceed one. If this is

the case, the rule of thumb value is switched to .5 for the maximum acceptable h_{ii}.

"Internally studentized residuals" were used to determine outliers with respect to Y. The following equation can be used to produce internally studentized residual values:

$$e \,/\, [MSE(1 - h_{ii})]^{.5} \qquad (3)$$

If this value exceeds the t-value associated with 10% alpha and n - P degrees of freedom, the data point is an outlier. SAS has a function which prints out the internally studentized residuals

There are numerous possible causes for these extreme values in the data:

1) The outlier data point belongs to a different population.

2) The independent variable data includes measurement error.

3) There was some unique major event with significant impact on the data.

4) Significant independent variables are excluded from the model.

5) The data point just so happens to fall in a tail of the data distribution.

6) The model is improperly specified.

7) The error terms come from non-normal distributions.

What one decides to do about the outliers depends upon their cause(s) and their influence. If one determines that an outlier belongs to another population, it can be thrown

out. If there are an insignificant number of outliers compared to the sample size, they can be thrown out. If the outliers are needed, due to the sample size, and they are non-influential, they can be left alone. If they are needed and influential, an attempt must be made to adjust the outliers to minimize their effect on the model.

To determine if an outlier is influential, SAS produces three measures of influentiallity: 1) DFFITS, 2) DFBETAS, and 3) Cook's Distance.

DFFITS values measure the influence of "case i" on the "fitted value" of condemnation costs and it can be calculated with the following equation:

$$(\text{DFFITS})_i = d^*_i \, (h_{ii}/(1 - h_{ii}))^{.5} \qquad (4)$$

(Neter, Wasserman, and Kutner, 1989:401)

The rule of thumb for this equation is that the absolute value of DFFITS may not exceed one for small to medium sized data sets and $2(P/n)^{.5}$ for large data sets.

DFBETAS values measure "the influence of the ith case on each regression coefficient b_k" and can be calculated as follows:

$$(\text{DFBETAS})b_k = b_k - b_{k(i)} \;/\; (MSE_{(i)}C_{kk})^{.5} \qquad (5)$$

(Neter, Wasserman, and Kutner, 1989:402)

where

C_{kk} is the kth diagonal element of $(X'X)^{-1}$

The rule of thumb for DFBETAS is that its absolute value may not exceed $2/(n)^{.5}$.

Cook's Distance is "an overall measure of the combined impact of ith case on all of the estimated regression coefficients" and it can be calculated with the following equation:

$$D_i = (b - b_{(i)})'X'X(b - b_{(i)}) \ / \ pMSE \qquad (6)$$

(Neter, Wasserman, and Kutner, 1989:403)

where

b is the vector of estimated regression coefficients obtained when all n data points are used.

$b_{(i)}$ is the vector obtained when the ith case is omitted.

The rule of thumb for Cook's Distance can be found by comparing it to the F distribution value for the fiftieth percentile with numerator degrees of freedom equal to the number of regression coefficients (p) (including the intercept term) and denominator degrees of freedom equal to n - p. If the Cook's Distance value exceeds the F distribution value the point is considered an influential outlier.

Multicollinearity. Multicollinearity is a violation of the assumed independence between the independent variables. As multicollinearity is introduced to a model the variance of the regression coefficients become very large and the coefficient values themselves become highly unstable. They may even take on the wrong

sign. As a result, the predicted coefficient values are more likely to be further from the true population parameter values and the variables' t-values may get smaller.

SAS provides several functions to test for multicollinearity in addition to the symptoms mentioned above. Pairwise correlation matrices, tolerance values and the SAS COLLINOINT function can be used. A pairwise correlation matrix shows the collinearity between two variables. The tolerance values depict multicollinearity between a variable and the rest of the model. The COLLINOINT function is a good method to use if the number of cost drivers exceeds four. For each variable a "condition number" is given. If this number exceeds ten, then a significant degree of multicollinearity is present. After identifying a variable with multicollinearity, one looks to the "variance proportions" listed for each remaining cost driver to determine what variables are contributing to the multicollinearity.

Heteroscedasticity. Heteroscedasticity is a violation of the assumption that the error terms come from distributions with constant variance. To check for this problem, the residuals can be plotted against the expected value of condemnation costs. If heteroscedasticity is present, the residual pattern will either converge or diverge as the expected condemnation cost values increase. If the spread of residuals remains relatively constant, one may assume that heteroscedasticity is not present.

Model Predictive Capability. After completing the diagnostic checks described above, the best linear model, the best arithmetic transformation model and the two best log-log transformation models were used to predict the condemnation costs for an MDS database excluded (for this purpose) from the original data set. The predicted values were compared to the actual values to see how well the models performed.

Model Sensitivity. The best linear model, best arithmetic transformation model and two best log-log transformation models were also tested to see how sensitive they were to changes in the values of independent variables. This was accomplished by first using the models to predict condemnation costs for several aircraft MDS. Then new estimates were created after increasing the value of one independent variable in each MDS by twenty percent (and leaving the other independent variable values alone). After repeating this action for each of the models' independent variables and noting the impacts on the condemnation costs estimates, the process was repeated except that the independent variable values were decreased by twenty percent.

Small Database Performance. Only those independent variables dealing with component utilization changed over time (e.g., sorties, number of aircraft in MDS inventory). It was anticipated that reducing the database by replacing these annual variable values (five data points

for most of the variables) with their MDS averages might provide a more statistically significant model if the individual values varied greatly within an MDS. However, this smoothing effect might also lead to unrealistic confidence in the models' ability to predict an annual spares requirement. This database smoothing technique was tested as the final analysis step.

<u>Demand Volatility Factor CER</u>

The SIV model for demand volatility was developed by regressing annual replenishment spares requirements data against annual condemnation costs for the same MD data set. By restricting the Y-intercept to equal zero, the demand volatility factor is simply the value of the regression coefficient from the resulting CER. In order to look at the statistical measures associated with the CER, another model w s created with no restriction on the Y-intercept. No logical explanation was found for any relationship between replenishment spares and condemnations other than a direct linear one and therefore no transformations of the condemnations data were considered.

The demand volatility factor currently used in the HQ AFLC/FMC Logistic Support Cost model was arrived at by comparing condemnations with replenishment spares obligations and simply averaging the various MDS ratios to come up with a standard factor. As mentioned in Chapter II, there are numerous factors which discredit the use of

obligations data in model development. Using scrubbed replenishment spares requirements generated by the D041 system is an improvement over the obligation data. Additionally, using SAS to derive the CER provided information on the statistical significance of the relationship--something not found in a straight ratio of replenishment spares obligations to condemnation costs.

In addition to the SAS produced CER, however, annual demand volatility factors were calculated by dividing annual MDS replenishment spares requirements by annual MDS condemnations costs. These results were analyzed for any year-to-year trends in MDS specific demand volatility factors. Additionally, demand volatility factors were considered for different mission categories (e.g., fighter, bomber, etc.).

Before the replenishment spares and condemnations data could be compared, however, there were several steps which had to be taken to ensure (as much as possible) that apples were being compared to apples, and not oranges. For example, it was already mentioned that the Weapon System Cost Retrieval System (WSCRS) condemnation data was provided in FY 91 dollars and that the scrubbed D041 replenishment spares requirements had to be inflated from then-year to FY 91 dollars. The WSCRS system inflates prior year condemnations to FY 91 dollars using separate escalation rates (obtained from AFR 173-13) for engine material, avionics material, and airframe material (AFLCM 173-264,

1990:136). Because the replenishment spares requirements data was aggregated at the MD level, the best that could be done was to inflate the data using the 3080 Other Procurement inflation rates (also obtained from AFR 173-13).

Two additional factors had to be accounted for in order to compare the replenishment and condemnation spares requirements data sets. First, the scrubbed D041 replenishment spares requirements included separate categories for "common spares," and the F100 and F110 engine spares (used in the F-15 and F-16 aircraft); while the WSCRS system had already distributed the condemnations costs for these categories among the relevant MDS.

The WSCRS system can split out for each MD what percent of the annual condemnations costs are MD unique and what percent are common to other MDs. An attempt was made to distribute the scrubbed D041 replenishment spares "common spares" category using these WSCRS MD percentages. For example, if the WSCRS system showed that fifty percent of an MD's condemnation costs were MD unique, it was assumed that the replenishment spares requirement for that MD represented only fifty percent of the total replenishment spares requirement also, and the remaining fifty percent must be included in the "common spares" requirements pool. It became apparent that there was a definitional difference in the term "common spares" between the D041 and WSCRS systems. Using the WSCRS ratios suggested that annual common spares allocations should be significantly greater than the annual

common spares pools identified. Given no clear understanding of the exact problem, this methodology was abandoned.

The HQ AFLC Recoverable Spares Stock Fund Manager indicated that his office used factors developed by the Logistics Management Institute (LMI) to spread the common spares among the various aircraft MD when necessary. The LMI factors are used, not because they are believed to be perfect by any means, but because they represent the best methodology available (Rosenthal, 1991). The LMI factors provide the percentage of the common spares requirements attributable to each MD based upon quarterly MD buy requirements for the common components. The factors change from year to year and even from quarter to quarter depending upon the current status and projected buy requirements.

These factors were used to allocate the common spares to the individual MDs. It should be noted that of the seven sets of factors used (one for each data year), four sets were based upon end-of-March databases which estimated MD percentages for the same fiscal year (e.g., FY88 percentages were based upon end-of-March FY88 status); while another two sets used end-of-September status to project percentages for the following fiscal year (e.g., the FY82 percentages were developed based upon end-of-September FY81 status). The final factor set used end-of-March status in FY84 to predict the FY85 percentages. The fact that different quarters were used and that, in three cases, the percentages were

projected a year into the future, introduced additional uncertainty to the identification of trends between the fiscal years.

In order to spread the annual F100 and F110 replenishment spares requirements between the F-15 and F-16, annual engine flying hour data from the WSCRS system was used. This data set divided the total annual engine flying hours for each engine type between the two MDs. It was assumed that the number of engine flying hours for a particular engine drove the same ratio of replenishment spares in the F-15 as it did in the F-16. For example, if the F-15 was accountable for seventy five percent of the total engine flying hours, then it also received seventy five percent of the engine's replenishment spares requirements pool.

The second factor which had to be accounted for was the fact that replenishment spares are purchased lead time away from the year in which they will be actually used (according to predicted usage). Therefore the replenishment spares requirements should have been compared to the associated MD condemnation costs lead time away. For this analysis, an average lead time of two years was used to offset the replenishment spares requirements and condemnation costs data sets. For example, FY 1982 replenishment spares requirements were compared to FY 1984 condemnation costs. In order to smooth the error introduced by this approach, an additional comparison was made between the total (all FYs)

condemnations costs for each MD and the associated total (all FYs) replenishment spares requirements.

Meeting the Research Objectives

In designing the condemnations cost model, relationships between cost and potential cost drivers taken from aircraft performance and physical characteristics were evaluated. It was thought that these relationships could offer a great improvement over historical factor-based models using aircraft flyaway costs. They offer insight into those factors which actually "drive" the cost of recoverable spares.

The condemnations cost model had to pass the diagnostics tests described earlier if it was to be accepted as a valid cost prediction model. In reality, one should never expect to obtain a "perfect model" that passes all tests with flying colors. For example, multicollinearity is a very common issue because the cost drivers being evaluated are all common to the weapon system for which the model is being designed. This commonality breeds multicollinearity! In the end, the analyst must use his or her professional judgement in compromising between the various diagnostics results to come up with a reasonable model. The general criteria which were established as goals for the research are summarized below:

1) The models' R^2 should be greater than or equal to 80%. Their adjusted R^2 is should be within 20% of R^2.

2) Confidence levels for the models' significance should be greater than or equal to 80%.

3) P-values should be relatively small (no rule of thumb).

4) Prediction intervals should not widen dramatically at outer bounds of the sample distribution.

5) Residual plots for the cost drivers should be random.

6) Outliers should be minimal and their influence reduced through proper data adjustment.

7) The impact of multicollinearity should be minimal.

The demand volatility factor CER was developed to see if a statistically significant SIV model could be developed using condemnation costs as the independent variable. The same seven criteria listed above were applicable to this model.

IV. Analysis and Findings

Introduction

This chapter presents the analysis and findings generated by the procedures described in Chapter III, "Methodology." The discussion is divided into two main sections beginning with the condemnation CERs analysis and ending with the demand volatility factor analysis. Within the condemnation CERs section, the results from four models are presented: the best linear model, the best arithmetic transformation model, the second best log-log transformation model, and the best log-log transformation model. The demand volatility factor section contains both the SAS generated SIV model results and analysis of spreadsheet generated demand volatility factors.

Condemnation CERs

The four models in this section were developed using the procedures described in Chapter III, "Methodology." Instead of providing a single "best" model, the best linear, arithmetic transformation and log-log transformation models are presented. Although evaluations are not presented for all the models tested in reaching the best model (the second log-log transformation model in this case), these four models show how the model performance changed as different types of transformations were attempted.

Tables 3 and 4 provide a condensed look at the data used in the development of these models. While the data in

Table 3

MDS Averages for Annual Data

MDS	AVG ANNUAL CONDEMN COSTS	AVG ANNUAL # OF MDS	AVG ANNUAL FLY HRS	AVG ANNUAL FLY HRS PER MDS	AVG ANNUAL # OF SORTIES
F15A	47,134,882	317	72,583	229.25	
F15B	8,797,006	54	13,602	253.82	
F16A	61,525,807	606	169,8[illegible]5	280.70	122,246
F4D	17,702,001	468	98,6[illegible]8	210.75	71,363
F4E	18,968,917	608	145,1[illegible]1	238.19	110,123
A7D	12,667,978	389	95,804	246.68	59,341
A7K	1,110,592	30	7,5[illegible]3	249.34	2,826
A10A	21,580,794	654	220,953	338.07	105,629
F111D	14,226,418	85	17,0[illegible]5	201.17	7,476
T37B	5,830,023	689	272,1[illegible]1	397.02	196,644
T38A	14,560,060	897	334,238	373.80	248,339
B52G	49,673,391	173	65,540	378.83	8,980
B52H	20,689,628	96	36,523	378.88	4,842
C5A	41,076,959	77	46,674	606.59	8,537
C130B	3,393,740	94	37,355	397.51	17,466
C130E	14,515,170	296	163,935	556.65	85,617
C141B	48,950,346	268	284,354	1,062.72	68,047
C135A	62,641,457	599	200,259	333.99	45,669
FB111A	13,878,724	69	17,335	252.43	4,832

Table 3 provide MDS averages for variables which change over time, annual (fiscal year) data was used in the actual model development. Appendix D provides the data as it was used in the model development.

Best Linear Model. None of the linear models tested provided very good statistical results. Among the many problems identified in the models, a universal issue was that the criterion for R^2 (80%+) was not achieved.

Table 4

MDS Data Used in Model Development

MDS	DUMMY	Empty Weight	Thrust Per Engine	Takeoff Over Empty Weight	Flyaway Cost	ENG #	Length Plus Span	Max Speed	Takeoff Weight	Max Load Factor	Max Climb Rate	Max Combat Radius
F15A	0	26,749	23,830	2.09	26,104,418	2	106.56	1,309	56,000	7.33	61,340	515
F15B	0	26,832	23,830	2.09	26,104,418	2	106.56	1,309	56,000	7.33	59,930	502
F16A	0	15,306	23,830	2.31	11,646,586	1	82.28	1,181	35,400	9.00	60,288	693
F4D	0	28,873	17,000	2.06	8,433,735	2	96.60	1,210	59,483	6.50	55,600	783
F4E	0	30,328	17,900	2.04	10,140,562	2	101.40	1,245	61,795	7.75	49,800	741
A7D	0	19,733	14,250	1.99	8,734,940	1	84.80	608	39,325	7.00	8,000	600
A7K	0	21,300	14,500	1.97	16,767,068	1	87.42	569	42,000	7.00	9,485	282
A10A	0	21,541	9,065	2.31	8,734,940	2	110.50	362	49,774	7.33	6,203	351
F111D	0	46,949	20,840	2.13	39,859,438	2	136.47	1,262	100,000	7.00	45,000	1,270
T37B	0	4,067	1,025	1.67		1	63.10	357	6,800	6.67	3,600	167
T38A	0	7,410	3,850	1.59		2	71.60	709	11,761	7.33	33,300	305
B52G	1	180,041	13,750	2.71	54,819,277	8	346.90	549	488,000	2.00	8,243	3,118
B52H	1	184,291	17,000	2.65	60,240,964	8	345.30	547	488,000	2.00	9,628	3,747
C5A	1	320,085	40,805	2.40	139,959,839	4	470.50	495	769,000	2.50	5,580	2,519
C130B	1	72,300	9,388	1.87	18,172,691	4	230.40	330	135,000	3.00	4,420	1,549
C130E	1	73,804	9,388	2.37	10,943,775	4	230.40	317	175,000	3.00	4,060	1,866
C141B	1	140,882	21,000	2.29	34,437,751	4	328.40	493	323,100	2.50	6,300	2,366
C135A	1	97,030	13,750	3.10		4	267.00	527	300,800	2.00	6,350	1,613
FB111A	0	47,481	20,350	2.51	39,658,635	2	145.54	1,262	119,243	3.00	33,800	

Additionally, C.V.s were universally high (40%+). Despite these less than awe inspiring results, the "best" linear CER is provided for comparison with the transformed models. This CER is expressed in the following equation:

$$\text{CONDEMN} = -103{,}454{,}577 + 149.20001(\text{SORT}) + 1{,}047.701346(\text{THRUST}) + 45{,}649{,}536(\text{TOEMPWT}) \quad (7)$$

where

CONDEMN = annual condemnations requirement ($)

SORT = MDS annual sorties

THRUST = maximum thrust per engine (lb)

TOEMPWT = maximum takeoff weight (lb)/maximum empty weight (lb)

An immediate flaw in this CER is fairly obvious. The large, negative Y-intercept term allows this model to predict negative annual condemnation requirements for those MDS with small cost driver inputs (particularly those with small TOEMPWT). Additional statistical information can be found in Table 5, which provides the SAS analysis of variance (ANOVA) results for this CER.

Looking at the positive attributes of this model, each of the cost drivers are significant to the 99.9% level and possess the correct sign. The adjusted R^2 is close to the R^2 value, indicating, once again, that all the variables are making significant contributions to the model and aren't included simply to drive up the R^2. Additionally, the overall model has a very low P-Value (.0001). Finally, the model is parsimonious in its selection of cost drivers.

Table 5

Linear Model Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	2.0833471E16	6.9444903E15	57.013	0.0001
Error	66	8.0391021E15	1.2180458E14		
C Total	69	2.8872573E16			

Root MSE	11036511.0996	R-square	0.7216
Dep Mean	26944355.4429	Adj R-sq	0.7089
C.V.	40.96038		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob>|T|
INTERCEP	1	-103454572	10464398.517	-9.886	0.0001
SORT	1	149.200010	22.42411015	6.654	0.0001
THRUST	1	1047.701346	180.16734946	5.815	0.0001
TOEMPWT	1	45649536	4066074.0692	11.227	0.0001

Unfortunately, the model has a more extensive list of negative attributes. Although the model appears to be significant and parsimonious, its R^2 value (.7216) does not pass the model acceptance criterion. This low value implies that there may be other sources of error not accounted for by the model.

The C.V. value (40.96038%) doesn't instill confidence in the model's predictive accuracy. Since one knows that the prediction interval will only get wider as one attempts to predict farther from the center of the data, one would be justified in stopping at this point. For completeness of analysis, however, the prediction intervals for every data

point were examined to record how the interval widths varied across the data. The smallest bound (using the SAS provided 95% bounds) for the data set was plus or minus $22,249,322. The largest bound in the data set was plus or minus $24,161,129. One can infer from these numbers that, percentage wise, the bounds do not increase dramatically as one moves from the center of the data to the outer edges of the data. Unfortunately, the interval was poor to begin with, so this information provides little benefit.

Another test was performed to determine how the model's prediction intervals were impacted by varying the level of confidence used in the model development. Figure 1 shows the predicted condemnations cost for the datapoint closest to the center of the data (i.e., the datapoint with the smallest prediction interval) and its associated upper and lower bounds for four different levels of confidence (70%, 80%, 90%, and 95%).

This figure allows one to see the magnitude of prediction interval growth as one's confidence level moves from 70% (plus or minus $11,641,289) to 95% (plus or minus $22,249,322). If one is attempting to predict costs for a datapoint away from the center of the data, and do so with a high confidence level, one can expect a very large prediction interval.

The ANOVA based analysis was only the beginning of the diagnostics performed on each CER. The following subsections address the complete line of diagnostic checks performed.

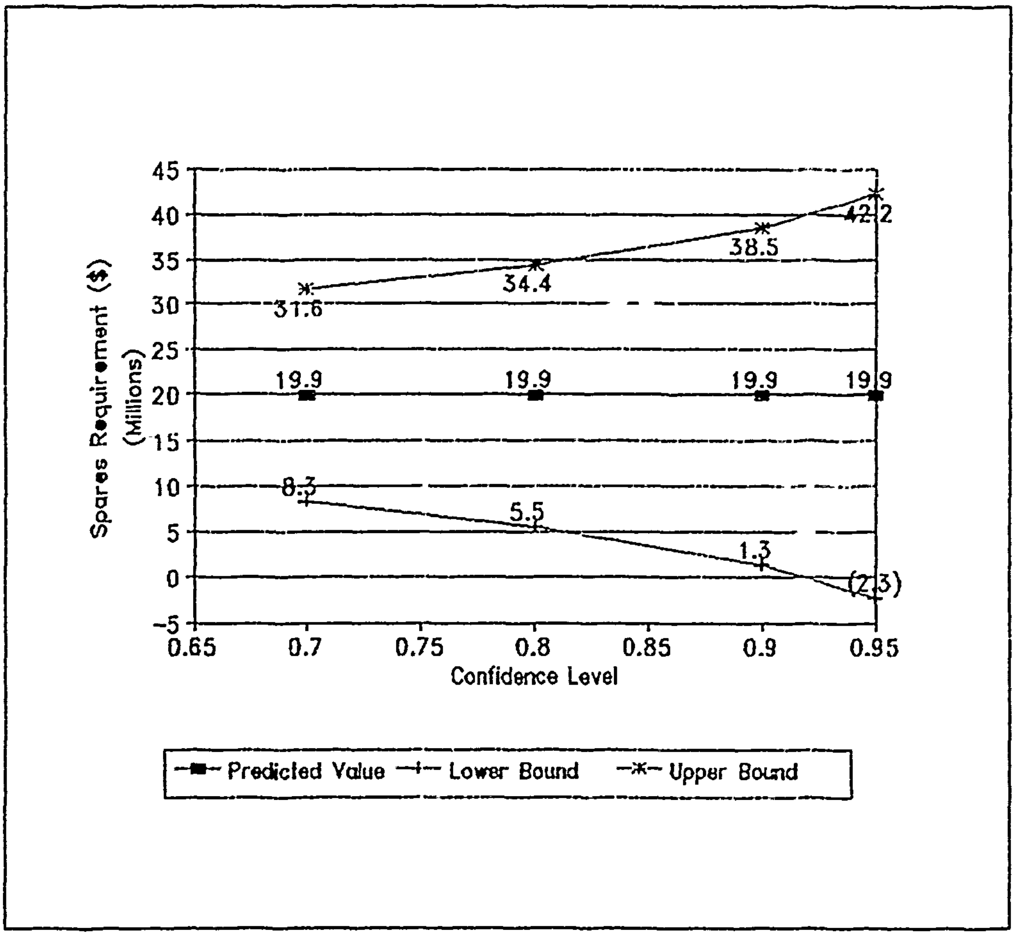

Figure 1. Linear Model Confidence Level Sensitivity

<u>Residual Plots</u>. For each cost driver, data point residuals were plotted against their corresponding cost driver values in an attempt to identify necessary variable transformations. In every case tested, the plots appeared to be randomly scattered. Normally this is exactly the results one hopes to achieve, because it indicates that the variables are properly specified. It was anticipated that variables such as "number of sorties" and "number of aircraft" would have direct linear relationships; but for those variaoles dealing with the intensity of parts

utilization and parts performance, transformations were logically expected. Therefore the "random plots" were attributed to noise in the data and two additional residual plot tests were performed: 1) partial regression plots and 2) omitted variable residual plots.

For these plots, one hopes to see a pattern in the residuals, because the pattern (be it linear, or some sort of non-linear pattern) signifies that the independent variable does, in fact, have a relationship with the dependent variable. Two variables were removed from the "best" linear model because these residual plots show no patterns in the data. This action was also confirmed by improvement in the model's significance. The only non-linear pattern identified is that reproduced in Figure 2. The partial regression residual plot for the variable "maximum takeoff weight/maximum empty weight (TOEMPWT)" displays residuals increasing at an increasing rate as the TOEMPWT values increase. The KC-135 data points at the extreme right in the graph appear to compose a separate grouping from the rest of the data points. The nature of the cargo and mission (aerial refueling) for this aircraft may provide unique design considerations that make this MDS an outlier with respect to the Y variable. The pattern seen in Figure 2 suggests that TOEMPWT should either be transformed using a positive exponent greater than one (an exponent value of two was used) or a log-log transformation should be used for the entire model.

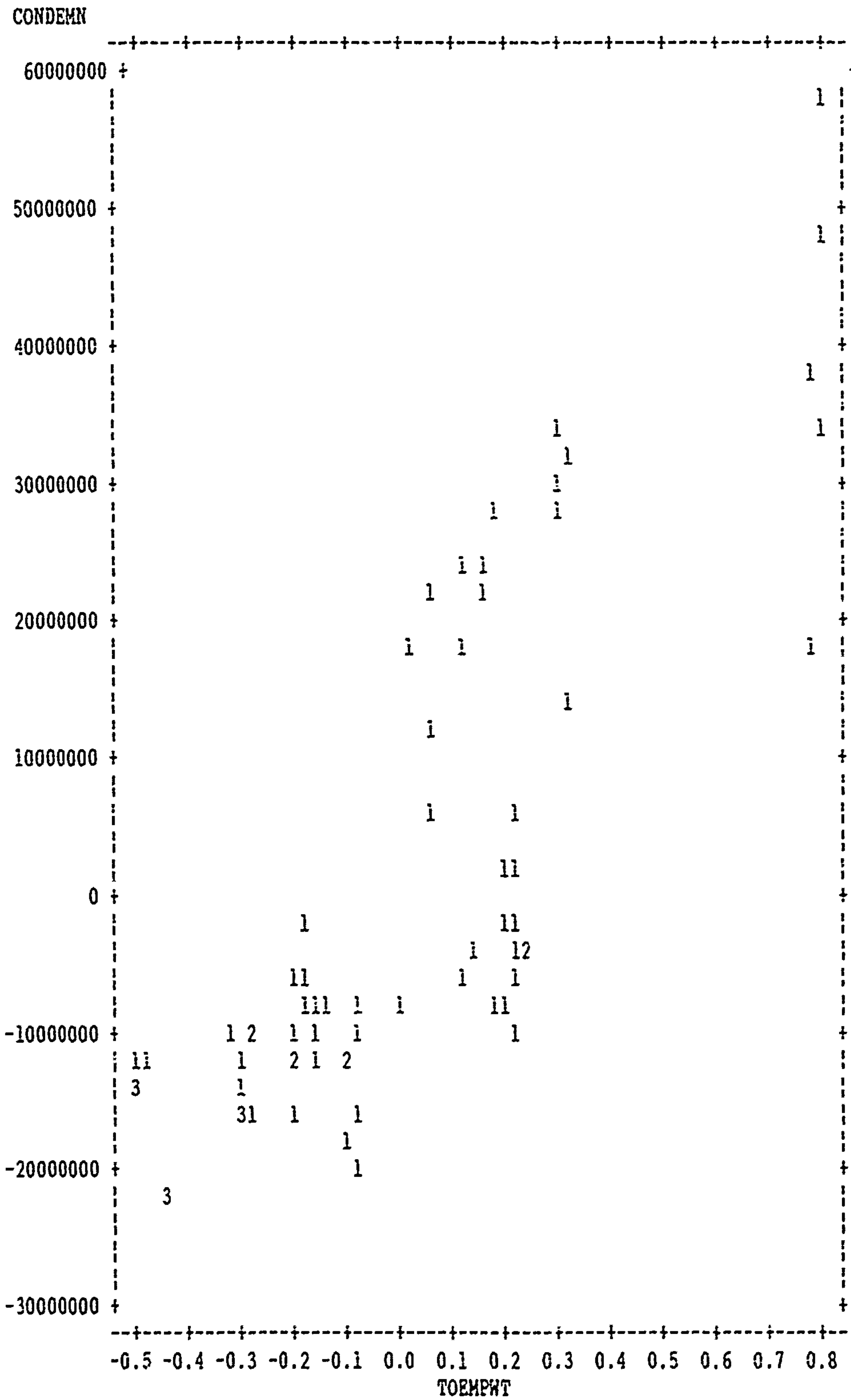

Figure 2. Linear Model Partial Regression Residual Plot

Outliers. The KC-135 was not the only MDS with datapoints that were outliers. Seventeen of the seventy data points had studentized residual values which classified them as outliers with respect to Y (the cutoff value being approximately 1.296). The MDS represented by these outliers include the F-16A, the B-52G and H models, the C-5A, the C-130E, the C-141B and the KC-135A. The leverage values for six datapoints indicated that these MDS were outliers with respect to X (the cutoff value being .1143). The MDS represented by these outliers include the T-38A and the C-5A.

Additional tests were run to determine how influential these outliers were. The results varied depending upon the test used. According to the Dffits test, five data points representing three MDS (F-16A, C-5A, and KC-135A) were identified as influential outliers with respect to Y (the cutoff value being .47804). Though this is a significant reduction from the earlier figure of seventeen, the number is still too high. By definition, outliers should represent an abnormality, not a common occurance. The Dfbeta test showed that four F-16A datapoints, one T-38A datapoint, two C-5A datapoints, one C-130B datapoint and three KC-135A datapoints were influential outliers (the cutoff value being .2390). The final influentiallity test, Cook's D, failed to identify any influential outliers.

Typically, one doesn't expect to see a large proportion of outliers within a data set. Outliers, by definition,

should not be the norm. However in this model a large number are identified. This phenomenon is at least partially explained by the wide variety of MDS represented in the model database. In attempting to develop an all-inclusive CER for aircraft condemnations requirements, noisy data became a byproduct of the model's generalizability.

After identifying the outliers the next issue was how to deal with them. According to acceptance criterion number six, the number of outliers should be "minimal" and their impact should be minimized through proper data adjustment techniques. However, in this case the broad population definition (all Air Force MDS meeting the "mature" weapon system criteria) made it impossible to simply drop datapoints for being outside the population. Additionally, no information was found which supported any type of data adjustment. Therefore, no action was taken to remove or adjust the outliers.

Multicollinearity. Both tolerance values and the SAS COLLINOINT function were evaluated to determine the impact of multicollinearity upon the model. Neither test showed any sign of a significant problem. The minimum tolerance value was .64698110 (with the cutoff being .10) and the maximum condition number was 2.00869 (with the cutoff being 10.0).

Heteroscedasticity. When datapoint residuals were plotted against predicted condemnation values (see Figure 3), a diverging pattern in the data indicated the presence

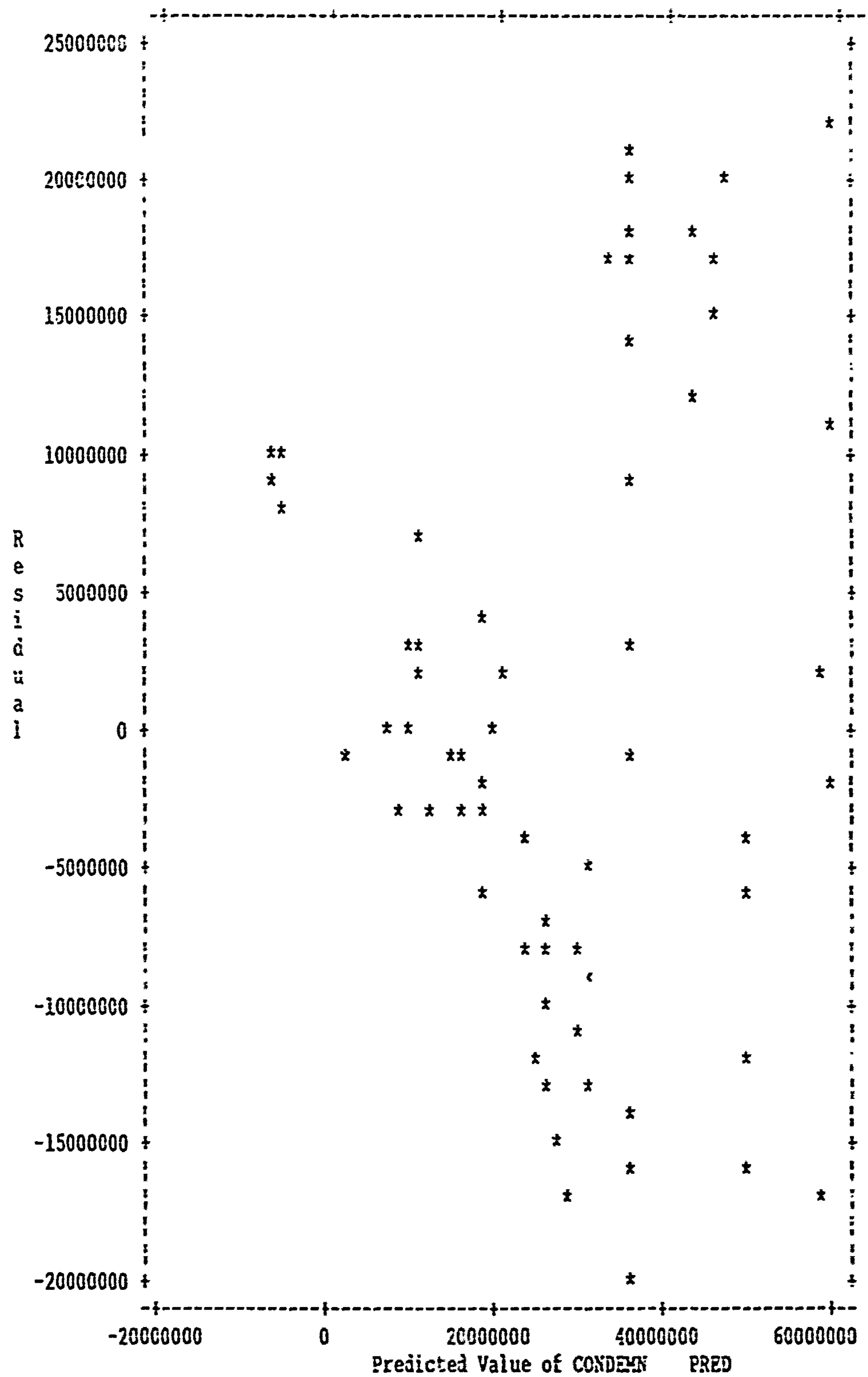

Figure 3. Linear Model Heteroscedasticity Test

of heteroscedasticity. Given the large number of problems already identified with this model, no attempt was made to correct for the apparent heteroscedasticity.

Model Predictive Capability. Table 6 shows how well the best linear model performed in predicting costs for datapoints outside the development database (see Appendix E for validation data set).

TABLE 6

Linear Model Validation Test Results

MDS	ACTUAL CONDEMN COSTS	BEST LINEAR ESTIMATE	Estimate Divided by ACTUAL
F16A	27,537,555	39,829,790	1.45
F4D	24,151,890	18,676,955	0.77
F4E	24,254,355	21,647,671	0.89
A7D	20,075,237	10,814,153	0.54
A7K	1,560,822	2,477,468	1.59
A10A	12,012,017	30,443,456	2.53
F111D	14,831,043	16,865,879	1.14
B52G	43,909,467	36,073,742	0.82
B52H	20,415,995	36,107,341	1.77
C5A	71,036,363	50,403,420	0.71
C130B	4,698,837	(5,223,867)	(1.11)
C130E	18,837,210	29,406,501	1.56
C141B	51,264,650	36,080,213	0.70
FB111A	13,471,819	26,930,368	2.00

As one might have guessed from the preceding discussion, this model did not come through the validation test with flying colors. As previously identified, the model predicts "negative" condemnations costs in some instances. In this case, the FY 1981 C-130B requirement is

estimated to be negative $5.2 million when the actuals were really $4.7 million. The largest absolute error (almost $21 million) is seen in the FY 1981 C-5A estimate. Although the F-4E estimate is within eleven percent of the actual, the average absolute percentage error among the fourteen estimates was 63.6 percent.

Model Sensitivity. Each model was also tested (with the same database used above) to determine how sensitive it was to changes in the values of its independent variables. The best linear model was relatively insensitive to a plus or minus twenty percent change in the "annual MDS sorties" variable. The average increase in the condemnation estimate was only 5.6 percent.

Adjustments to the second variable, "thrust per engine," provided mixed results. If the original condemnations cost estimate for an MDS is small relative to the size of the model's parameter estimate, variable value, or product of the two, it is dramatically impacted (percentage wise) by the plus or minus twenty percent adjustment. For example, the A-7K original condemnation costs estimate was only $2.48 million. The "thrust" parameter value, multiplied by the value for thrust, was 15.2 million. Increasing the "thrust" variable resulted in a new estimate that was 2.23 times the size of the original estimate. Over the entire data set, the average estimate change attributable to adjusting this variable was 24.3 percent.

Adjusting the third variable "maximum takeoff weight divided by maximum empty weight (TOEMPWT)," had the greatest impact upon the model estimates. For example, the original C-130B estimate was "negative" $5.2 million. Increasing the "TOEMPWT" by twenty percent resulted in a new estimate of $11.8 million. The A-7K estimate increased by 727 percent. Here once again the relative size of the parameter value compared to the original estimate made a difference. The parameter value was 45.65 million compared to an original estimate of only $2.48 million. The average estimate change attributable to adjusting this variable was 145.5 percent.

It is clear from these results that the linear model is extremely sensitive to the TOEMPWT variable. The large parameter values in this model led to greater percentage changes in the estimates than the percentages used to adjust the variables. Appendix F contains the complete results of the sensitivity test for the linear and arithmetic transformation models.

Small Database Performance. The final test run on each model was to reduce the model development database by replacing annual MDS values (for those variables which changed over time) with a single MDS average. This test was performed to evaluate the impact of data smoothing on the model statistics.

Upon condensing the best linear model's database, most of the statistics were actually degraded. The model's F-Value fell from 57.013 to 12.34. The C.V. rose from 40.96

to 45.20. Only the R^2 improved slightly from 72.16 percent to 74.01 percent. Additionally, the data smoothing did not aide in the interpretation of residual plots as had been hoped. Given that this type of data smoothing did not improve the model performance, no further analysis was performed using the smaller data set and this linear model.

Best Arithmetic Model. In general the arithmetic transformations did not fair much better than the linear models. In two instances, extremely high R^2s (92%+) and relatively low C.V.s (19% and 24%) were obtained; but both of these models involved extremely high multicollinearity and counter-intuitive parameter signs. The "best" arithmetic transformation includes the same variables as those in the "best" linear model; but the "maximum takeoff weight divided by maximum empty weight" variable is squared (one of the transformations indicated by the linear model partial regression residual plot). The arithmetic equation for this CER is as follows:

$$\text{CONDEMN} = -50{,}924{,}161 + 141.626044(\text{SORT}) + 1{,}140.836199(\text{THRUST}) + 9{,}469{,}327(\text{TOEMPWT2}) \quad (8)$$

where

CONDEMN = annual condemnation requirement ($)

SORT = MDS annual sorties

THRUST = maximum thrust per engine (lb)

TOEMPWT2 = (maximum takeoff weight (lb)/maximum empty weight (lb))^2

A standard quadratic equation was also attempted which included both the TOEMPWT and TOEMPWT2 terms; but this model's performance measurements were inferior to the model using TOEMPWT2 alone.

The transformation of TOEMPWT to TOEMPWT2 did not have a great impact upon the model's performance relative to the linear model. Once again, this model is capable of predicting negative condemnation costs due to the large, negative Y-intercept. The absolute value of the term is less than one half that of the linear model's Y-intercept but it still is a large negative number. This model's ANOVA statistics are also similar to the linear model's. Table 7 provides the SAS ANOVA table.

Table 7

Arithmetic Transformation Model Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	2.09961E16	6.9987E15	58.645	0.0001
Error	66	7.8764732E15	1.193405E14		
C Total	69	2.8872573E16			

Root MSE	10924307.8761	R-square	0.7272
Dep Mean	26944355.4429	Adj R-sq	0.7148
C.V.	40.54396		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob>¦T¦
INTERCEP	1	-50924161	6306361.7189	-8.075	0.0001
SORT	1	141.626044	21.89513677	6.468	0.0001
THRUST	1	1140.836199	177.95185884	6.411	0.0001
TOEMPWT2	1	9469327	830485.53975	11.402	0.0001

The good qualities of this model mirror those of the linear model. Each of the cost drivers are significant to the 99.9 percent level and they all possess the anticipated positive sign. The adjusted R^2 value is very close to the R^2 value and the overall model's P-Value is very low (.0001). This model is also parsimonious in its use of cost drivers.

Unfortunately, this models shares the same negative ANOVA attributes as well. The R^2 is only negligibly higher at 72.72% (compared to the linear model's 72.16%). The C.V. value is also only slightly improved (40.54396 compared to 40.96038). The prediction intervals did not increase significantly from the center of the data ($22,026,530) to the outer edges of the data ($23,918,251); but like the linear model, the prediction interval was already so large in the center of the data that this positive attribute is inconsequential.

Figure 4 illustrates how this model's prediction intervals are impacted by adjustments to the level of confidence used in the model development. The intervals decrease by almost fifty percent as one moves from the SAS provided 95% confidence level (plus or minus $22,026,530) to a 70% confidence level (plus or minus $11,524,720). These bounds, once again, are only slightly improved (smaller) over the linear model bounds.

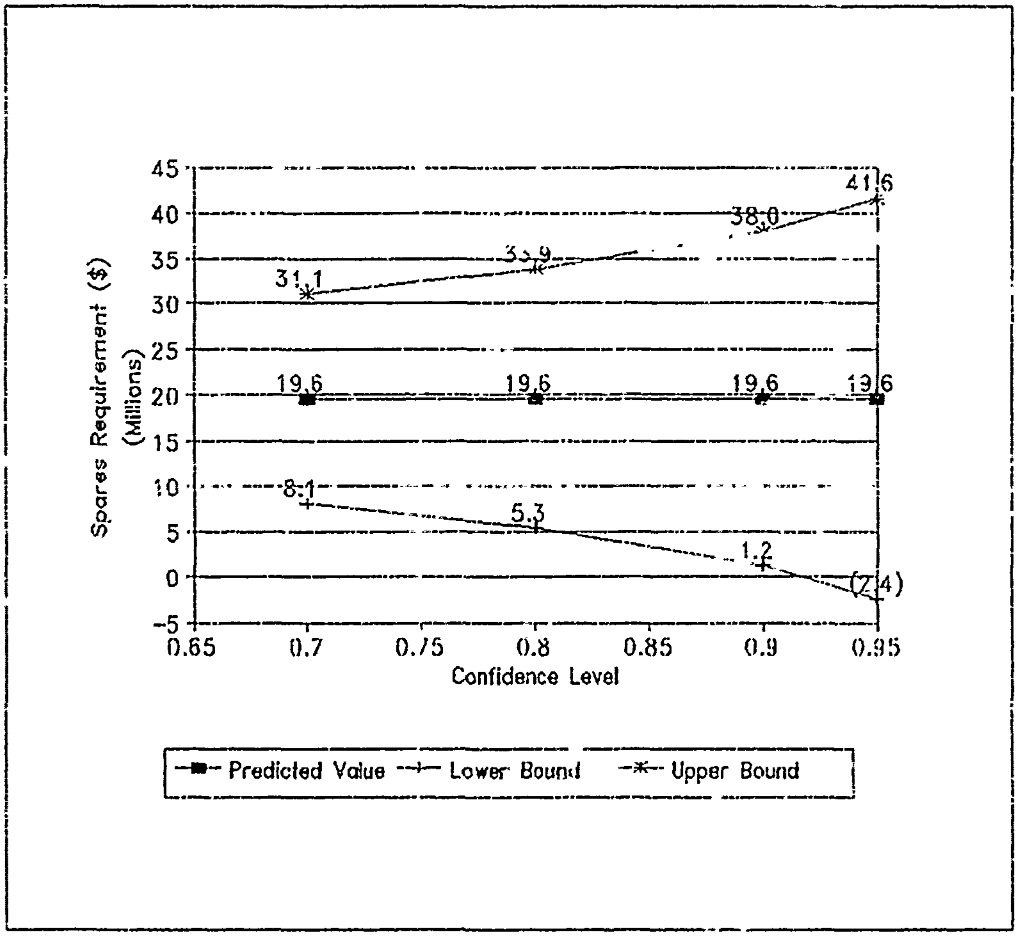

Figure 4. Arithmetic Transformation Model Confidence Level Sensitivity

Residual Plots. The same three forms of residual plots used on the linear model were applied to this model also. The plots were almost identical. In other words, the transformation of TOEMPWT did not significantly change the partial regression residual plot which had originally suggested the need for a transformation (Figure 2). If changing TOEMPWT to TOEMPWT2 had been the answer, one would expect the new plot to show a linear pattern. The second alternative to squaring the TOEMPWT variable was performing

a log-log transformation on the entire model. This type of transformation is discussed in the next model subsection.

Outliers. Seventeen of the seventy datapoints in the model development database were identified as outlier with respect to Y by their studentized residual values. With the exception of one C-5A datapoint being swapped for a C-141B datapoint, these outliers were the same as those identified in the linear model analysis. The databases used to develop the two models are identical, except for the TOEMPWT values which are squared in this model; and because the number of variables are the same, the cutoff values used in the various outlier tests are also the same.

The different outlier influentiallity tests provided mixed results. The arithmetic transformation model's Dffits test identified six data points as being influential outliers with respect to Y. The T-38A was the sole addition to the linear model's list of MDS containing these outliers (F-16A, C-5A, and KC-135A). The Dfbeta test showed that four F-16A datapoints, one T-38A datapoint, three C-5A datapoints, and three KC-135A datapoints were influential outliers. All but two of these datapoints were identical to the linear model's results. The Cook's D test failed to identify any influential outliers.

The outlier problem for this model was essentially the same as that in the linear model. As with all the models tested, no attempt was made to adjust the data due to a lack of information supporting appropriate adjustments.

Multicollinearity. Both the tolerance values and COLLINOINT condition numbers indicated that there was no significant multicollinearity problem in the model. The smallest tolerance value was .665 (with a cutoff value of .10). The largest condition number was 1.95 (with a cutoff value of ten).

Heteroscedasticity. The datapoint residual versus predicted condemnation value plot looked exactly like the linear model's corresponding plot (Figure 3). Once again, however, no action was taken to correct for the apparent heteroscedasticity.

Model Predictive Capability. Table 8 addresses the predictive capability of this model. The validation

TABLE 8

Arithmetic Transformation Model Validation Test Results

MDS	ACTUAL CONDEMN COSTS	BEST LINEAR ESTIMATE	Estimate Divided by ACTUAL
F16A	27,537,555	39,006,511	1.42
F4D	24,151,890	18,413,977	0.76
F4E	24,254,355	21,467,963	0.89
A7D	20,075,237	10,881,295	0.54
A7K	1,560,822	3,126,105	2.00
A10A	12,012,017	27,935,278	2.33
F111D	14,831,043	17,001,586	1.15
B52G	43,909,467	35,646,512	0.81
B52H	20,415,995	35,708,541	1.75
C5A	71,036,363	51,640,071	0.73
C130B	4,698,837	(4,224,276)	(0.90)
C130E	18,837,210	27,056,999	1.44
C141B	51,264,650	35,027,409	0.68
FB111A	13,471,819	26,312,317	1.95

data set found in Appendix E was run through the model to determine how well this model performed.

Just as in the linear model, the C-130B stands out like a sore thumb because the model predicts "negative" condemnation requirements. Because only living creatures regenerate their broken parts, this type of estimate would be difficult to sell. The largest absolute error was associated with the C-5A ($19.4 million). The average absolute percentage error among the fourteen estimates is 60.9 percent--a 2.7 percent improvement over the linear model.

Model Sensitivity. The arithmetic transformation model was relatively insensitive to the "MDS annual sorties" variable adjustment. Increasing this variable by twenty percent increased the condemnation cost estimates, on average, by only 6.79 percent. Adjusting the second variable, "thrust per engine," in the same way increased the condemnation cost estimates, on average, by 25.29 percent. A twenty percent increase in the third variable, "(maximum takeoff weight divided by maximum empty weight)^2," resulted in the largest average estimate increase--135.07 percent.

These estimate increases were similar to the linear model results. The first two variables were impacted slightly more in the arithmetic transformation model; but the third variable's average estimate increase was over ten percent less (in the arithmetic model). Because the third variable was the most sensitive of the lot, the arithmetic

model was, overall, less sensitive than the linear model. As seen in the linear model, those MDS with smaller initial condemnations costs were, percentage wise, impacted more severely during the sensitivity test.

Small Database Performance. Using the condensed database had practically the same impact on this model as it did the linear model. The R^2 value rose slightly from 72.72% to 74.63% but other statistics were degraded. The F-Value dropped from 58.645 to 12.749. The C.V. increased from 40.54396 to 44.65703. For these reasons, no additional analysis was performed with the small database.

Second Best Log-Log Transformation Model. As one could see in the preceding analysis, the linear and arithmetic transformation models were very similar in their performance. It wasn't until log-log transformations were used that significant improvements in the model statistics were achieved. It should be noted that direct comparisons between the two log-log models presented in this thesis and the preceding models are hampered by the fact that different databases were used in the development of the log-log models. The "MDS annual sorties" and "MDS flyaway cost" variables were incomplete for some MDS and therefore, depending on which variables were included in a model, the databases differed. The first log-log model's database excludes the T-37B, T-38A,and KC-135A datapoints (as found in the first two models) and adds FB-111A datapoints. The second log-log model discussed also excludes the same three

MDS; but in addition to the FB111A, its database includes F-15A and F-15B datapoints. The second log-log model is also the only one to contain five datapoints for all the MDS contained in its database (the other models contained a few MDS with less than five datapoints). Given that a generic aircraft spares model was being developed (i.e., not mission specific), it was considered more important to include as many MDS as possible in each model rather than restricting the models to a common database.

The mathematical equation for the second best log-log transformation model is expressed in the following equation:

$$\begin{aligned} \mathrm{CONDEMN} = {} & \mathrm{antilog}(-11.621185) * (\mathrm{SORT})^{.857977} * (\mathrm{HRSORT})^{.976842} * \\ & (\mathrm{SPEED})^{.557096} * (\mathrm{MAXLF})^{.525784} * (\mathrm{TOEMPWT})^{3.085454} * \\ & (\mathrm{FLYCOST})^{.696182} \end{aligned} \tag{9}$$

where

CONDEMN = annual condemnations requirement ($)

SORT = annual sorties

HRSORT = annual flying hours/MDS annual sorties

SPEED = maximum speed (kn)

MAXLF = maximum load factor (g's)

TOEMPWT = maximum takeoff weight (lb)/maximum empty weight (lb)

FLYCOST = flyaway cost ($)

Without going into the model's statistical performance, one improvement in this model, relative to its predecessors, is immediately apparent. Because this model has no large

negative Y-intercept term, it will always provide one with positive condemnation cost estimates.

Looking at Table 9, one can see that this model also has many statistical improvements over the linear and arithmetic transformation models. For example, the R^2 value (92.81%) for this model is the first to meet the acceptance criterion? established in Chapter III (80.0%). The adjusted R^2 value (92.08%) is very close to the R^2 value, indicating

Table 9

Second Best Log-Log Transformation Model
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	6	56.84300	9.47383	126.985	0.0001
Error	59	4.40173	0.07461		
C Total	65	61.24473			

Root MSE	0.27314	R-square	0.9281
Dep Mean	16.67773	Adj R-sq	0.9208
C.V.	1.63775		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob>|T|
INTERCEP	1	-11.621185	1.72285885	-6.745	0.0001
LSORT	1	0.857977	0.0438854	19.550	0.0001
LHRSORT	1	0.976841	0.19575726	4.990	0.0001
LSPEED	1	0.557096	0.08992126	6.195	0.0001
LMAXLF	1	0.525784	0.14409791	3.64	0.0006
LTOEMPWT	1	3.085454	0.53437101	5.74	0.0001
LFLYCOST	1	0.696182	0.09304748	7.82	0.0001

indicating that the increase in R^2 is not due simply to an influx of insignificant independent variables. In fact, all

of the individual variables are significant to the 99.9% level and the F-Value (126.985) more than doubles the previous models' statistics. Additionally, the overall model's P-Value is very low (.0001).

The model's Root MSE value (27.314%) also represents a significant improvement; but it still isn't as low as one would like to see. A figure closer to ten percent would have provided a much warmer feeling about this model's predictive accuracy.

The prediction interval varied significantly depending upon whether one was near the center of the data or not. Using the SAS 95% prediction interval bounds, it was noted that at the center of data the width of the prediction interval (converted to arithmetic space) was 11,324,214. At the outer edge of the data, the prediction interval width grew to 57,356,284--a difference of 6,032,070. Although this model is more sensitive to a datapoint's distance from the center of the data, one must remember that the previous models had poor intervals even in the center of the data. Being consistently bad is not an improvement. Only when one moves to the extreme high end of the data does the log-log model have larger prediction interval widths.

One must be careful when comparing prediction interval performance for a log-log model with that of a linear or arithmetic transformation model. Being at the center of the data in a log-log model does not guarantee that the arithmetic width of the prediction interval is the smallest

in the model (as it does in the linear and arithmetic transformation models). This datapoint's prediction interval, when converted to arithmetic space, is the smallest, percentage wise, relative to the predicted value of the dependent variable (Y). As will be seen in the second log-log model, if the center of the data is located nearer the larger predicted values for Y, the prediction interval can be rather large and still be, percentage wise, the best predictor of Y.

The only area in which this log-log model is weaker than its predecessors is in its "ease of application." This model has more cost drivers and therefore additional data must be gathered before it can be used. However, the variables were considered logical and they all tested to be significant. If one were to exclude significant variables simply for ease of application, one would have to accept a lower R^2.

The next test conducted was the confidence level sensitivity test. The center of the data was located in logarithmic space and then converted to arithmetic space. Figure 5 shows how the bounds (converted to arithmetic space) are impacted by varying the level of confidence. As in the previous models, moving the level of confidence from 70% to 95% had a tremendous impact on the prediction interval width. The width more than doubles from 5,698,179 to 11,324,210.

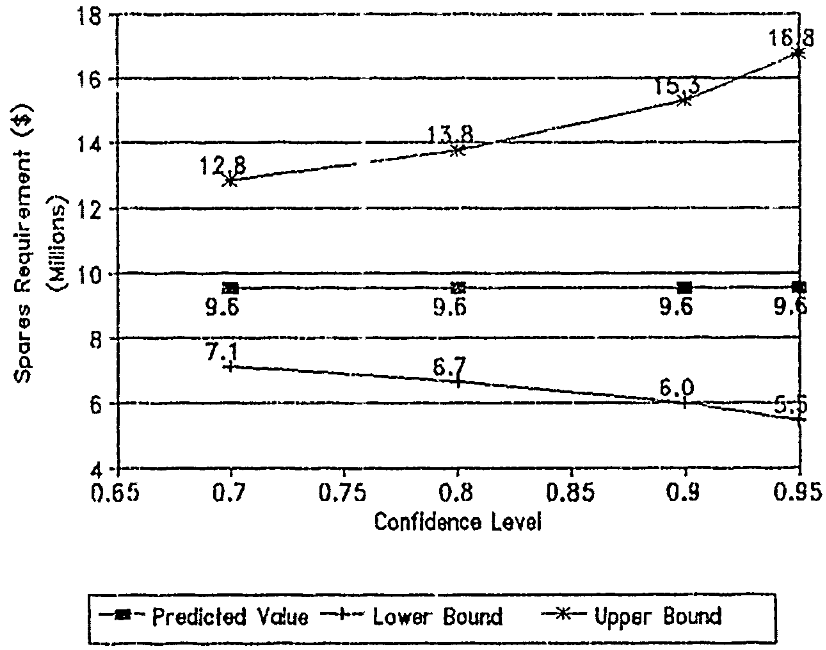

Figure 5. #2 Log-Log Transformation Model
Confidence Level Sensitivity

<u>Residual Plots</u>. The same three forms of residual plots used in the previous analysis were also used on the log-log models. Once again, all of the standard residual plots appeared to show randomly scattered datapoints. For this model, however, neither of the two additional residual plot forms identified the need for a variable transformation. The patterns in these plots appeared to be positively sloped and linear, indicating that the correct transformations had been found. It should be noted that the

data dispersion was greater for the "TOEMPWT" and "MAXLF" variables.

Outliers. Using a log-log transformation did not improve the outlier problem seen in the previous models. Fifteen of the 66 datapoints used in this model were identified as outliers with respect to Y by their studentized residual values. The MDS represented in these outliers included the F-4D, F-4E, A-7D, A-7K, B-52G, B-52H, C-130B, C-141B, and FB-111A. The leverage values for only one of the 66 datapoints indicated it was an outlier with respect to X. This was a C-5A datapoint. The percentage of outliers actually increased with this transformation.

The number of outliers which were influential was also high according to the Dfbeta test. Fifteen different datapoints were influential outliers for one variable or another according to this test. The MDS included in this category were the F-4D, F-4E, A-7D, A-7K, A-10A, C-130B, C-130E, C-141B, and FB-111A. The Dfits test, however, indicated that only four datapoints (including F-4E, C-130B, and A-7K datapoints) were influential outliers with respect to Y. The Cook's D test, however, revealed no influential outliers. Once again, no action was taken to alleviate the outlier condition.

Multicollinearity. Whether or not one believes there is a serious multicollinearity problem in this model depends upon which test's rule of thumb one has more faith in. The rule of thumb used for the tolerance test is that

each variables's tolerance value must be ten percent or higher. The "HRSORT" variable has a tolerance value of .07621283. The rule of thumb used in this thesis for the COLLINOINT test is that the highest condition number can be equal to or greater than ten. This model's largest condition number is 8.19456. Even if a large degree of multicollinearity exists, it doesn't necessarily mean that the model will not continue to predict in a consistent manner. If the multicollinearity is constant over time, such as when it is due to some physical law, the model will continue to predict as well as if the multicollinearity was not present. According to the COLLINOINT test, the multicollinearity relationship appears to be between the "flying hours per sorty," "maximum load factor," "ratio of maximum takeoff weight to maximum empty weight," and "flyaway cost" variables. Given the time constraints of this thesis, there was inadequate time to thoroughly study the relationship among these variables to determine if a constant relationship should be expected. Because the final log-log model (discussed in the next model subsection) did not appear to have a severe multicollinearity, no effort was made to adjust this model. Given the mixed results of the tests, and the possibility that the multicollinearity is constant over time, it hasn't really been determined that there is a need for any adjustment.

Heteroscedasticity. The "datapoint residual versus predicted condemnations plot" did not suggest the

presence of heteroscedasticity in this model. The scatter pattern maintained a fairly constant width across the data.

Model Predictive Capability. Table 10 shows how well this log-log transformation model performed in predicting costs for the validation data set (see Appendix E). Each estimate produced by SAS was multiplied by a bias adjustment factor of 1.038. The average absolute percent error among the fourteen estimates was 30.6 percent. This is a considerable improvement over the previous models' percent error (63.6 percent and 60.9 percent) and as was already stated, this model provides no "negative" cost

TABLE 10

#2 Log-Log Transformation Model Validation Test Results

MDS	ACTUAL CONDEMN COSTS	#2 Log-Log ESTIMATE	Estimate Divided by ACTUAL
F16A	27,537,555	39,235,008	1.42
F4D	24,151,890	14,723,360	0.61
F4E	24,254,355	21,934,295	0.90
A7D	20,075,237	9,165,037	0.46
A7K	1,560,822	1,690,062	1.08
A10A	12,012,017	25,926,341	2.16
F111D	14,831,043	13,946,359	0.94
B52G	43,909,467	39,742,968	0.91
B52H	20,415.995	25,424,376	1.25
C5A	71,036,363	45,137,070	0.64
C130B	4,698 837	2,881,839	0.61
C130E	18,837 210	15,197,728	0.81
C141B	51,264,650	59,692,585	1.16
FB111A	13,471,819	12,312,288	0.91

estimates. However, the largest absolute error was $25.9 million (for the C-5A), compared to $21 million and $19.4 for the previous models.

Model Sensitivity. Table 11 presents the results of the model sensitivity test. For each cost driver, the impact of a plus or minus twenty percent change in X (the cost driver value) is presented. As one can see, the model is relatively insensitive to changes in all the cost drivers except one "the ratio of maximum takeoff weight to maximum empty weight" (TOEMPWT). A twenty percent increase in this variable results in a 76 percent increase in the cost estimate. The only other variable which, when adjusted by twenty percent, caused a percent adjustment in the

Table 11

#2 Log-Log Transformation Model
Sensitivity Test

Variable	Delta Y due to increase in X	Delta Y due to decrease in X
SORT	+.17	-.29
HRSORT	+.19	-.20
SPEED	+.11	-.12
MAXLF	+.10	-.11
TOEMPWT	+.76	-.50
FLYCOST	+.14	-.14

condemnations estimate greater than twenty percent was the "annual sorties" variable. When the SORT value was multiplied by .8, the cost estimate decreased by 29 percent.

Small Database Performance. The condensed database test resulted in mixed results. The model's R^2 went up from 92.81 percent to 97.04 percent and the C.V. fell from 27.314 percent to 25.285 percent. These welcomed results were offset by the fact that the model's F-Value fell from 126.985 to 38.314. Additionally, the condition value on the COLLINOINT test went up to 9.8942. For these reasons, no further analysis was performed on the condensed data set model.

Best Log-Log Transformation Model. The "best" log-log transformation model was actually outperformed by the log-log model discussed above in several respects, but it was decided that its overall performance made this last model the best one developed during the analysis.

The mathematical equation for the "best" log-log transformation model is expressed in the following equation:

$$\text{CONDEMN} = \text{antilog}(-9.185307) * (\text{ACNUM})^{1.018916} * (\text{THRUST})^{.74345} * (\text{TOEMPWT})^{2.491597} * (\text{FLYCOST})^{.667079} \qquad (10)$$

where

CONDEMN = annual condemnations requirement ($)

ACNUM = annual number of aircraft in MDS inventory

THRUST = maximum thrust per engine (lb)

TOEMPWT = maximum takeoff weight (lb)/maximum empty weight (lb)

FLYCOST = flyaway cos ($)

Like the first log-log model just described, this model always provides positive estimates (i.e., the sign is positive). Since the superiority of the last log-log model over the linear and arithmetic transformation models was made clear in the last model subsection, the following text will focus on the comparison of the two log-log models.

Table 12 provides the ANOVA statistics for the "best" log-log transformation model. As previously stated, there are several statistics in which the first log-log model performs better than this model. For example, the first log-log model's R^2 value (92.81%) is slightly better than

Table 12

Best Log-Log Transformation Model
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	4	78.44007	19.61002	239.074	0.0001
Error	75	6.15187	0.08202		
C Total	79	84.59193			

Root MSE	0.28640	R-square	0.9273
Dep Mean	16.64209	Adj R-sq	0.9234
C.V.	1.72094		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob>|T|
INTERCEP	1	-9.185307	1.14373918	-8.031	0.0001
LACNUM	1	1.018916	0.05170451	19.707	0.0001
LTHRUST	1	0.743450	0.11291517	6.584	0.0001
LTOEMPWT	1	2.491597	0.44931709	5.545	0.0001
LFLYCOST	1	0.667079	0.08913384	7.484	0.0001

that of this model (92.73%). Both model's adjusted R^2s are close to their R^2, and so the overall difference in the R^2 statistic is minuscule. The first model's Root MSE (27.314%) is also slightly better than that of this model (28.640%). The individuals variables in both models are highly significant (99.9%) and they both have very small P-Values (.0001).

The first major difference in the models is in their F-Values. The "best" model's F-Value (239.074) almost doubles that of the first log-log model (126.985). This indicates that it is a more statistically significant model. The best log-log model also has two fewer cost drivers. This will make the data gathering process easier for this model.

The prediction interval analysis for the best log-log model was interesting in that the bounds widths behaved differently. Like the last model, the prediction interval varied significantly depending upon whether one was near the center of the data or not. Using the SAS 95% prediction interval bounds, one can see that at the center of data the width of the prediction interval (converted to arithmetic space) is 50,932,443. Though this interval is significantly wider than the first model's (11,324,212), this doesn't mean that the model will always have larger bounds. At the outer edge of the data (where X is the smallest), the prediction interval actually shrinks to a width of 4,142,632--a reduction of 46,789,811. The fact that this model's bounds

are wider in the center of the data simply means that the point at which this model predicts the best, percentage wise, occurs at higher estimated values of Y. The magnitude of the prediction interval change is actually only 758 thousand higher in this model.

Figure 6 displays the confidence level sensitivity test results. Like the other models, the results show that the

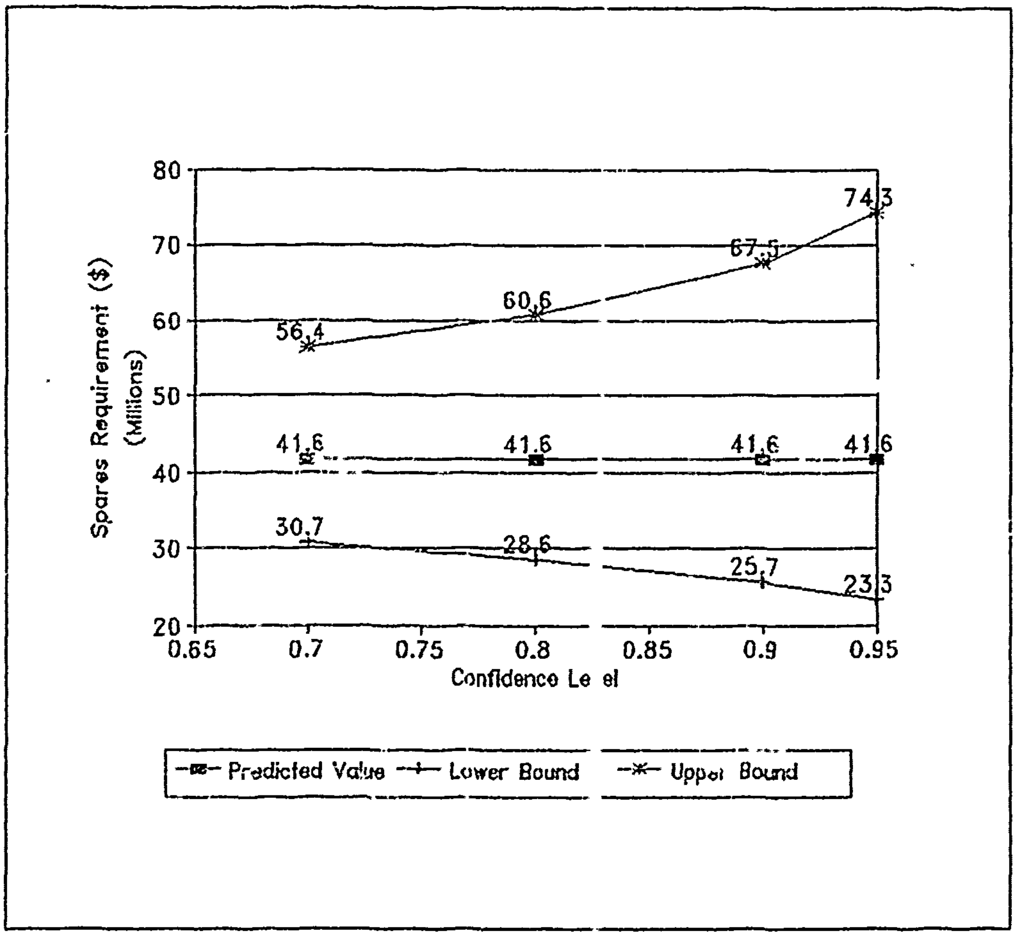

Figure 6. Best Log-Log Transformation Model Confidence Level Sensitivity

prediction interval almost doubles as the level of confidence increases from 70 percent to 95 percent. In

order to show the relative size of the various model's bounds when the same scale is used for all the models, one additional graph (Figure 7) was created. The bounds for the linear and arithmetic transformation models were essentially the same width and therefore, to make a cleaner graph, Figure 7 includes only the linear bounds. The two log-log

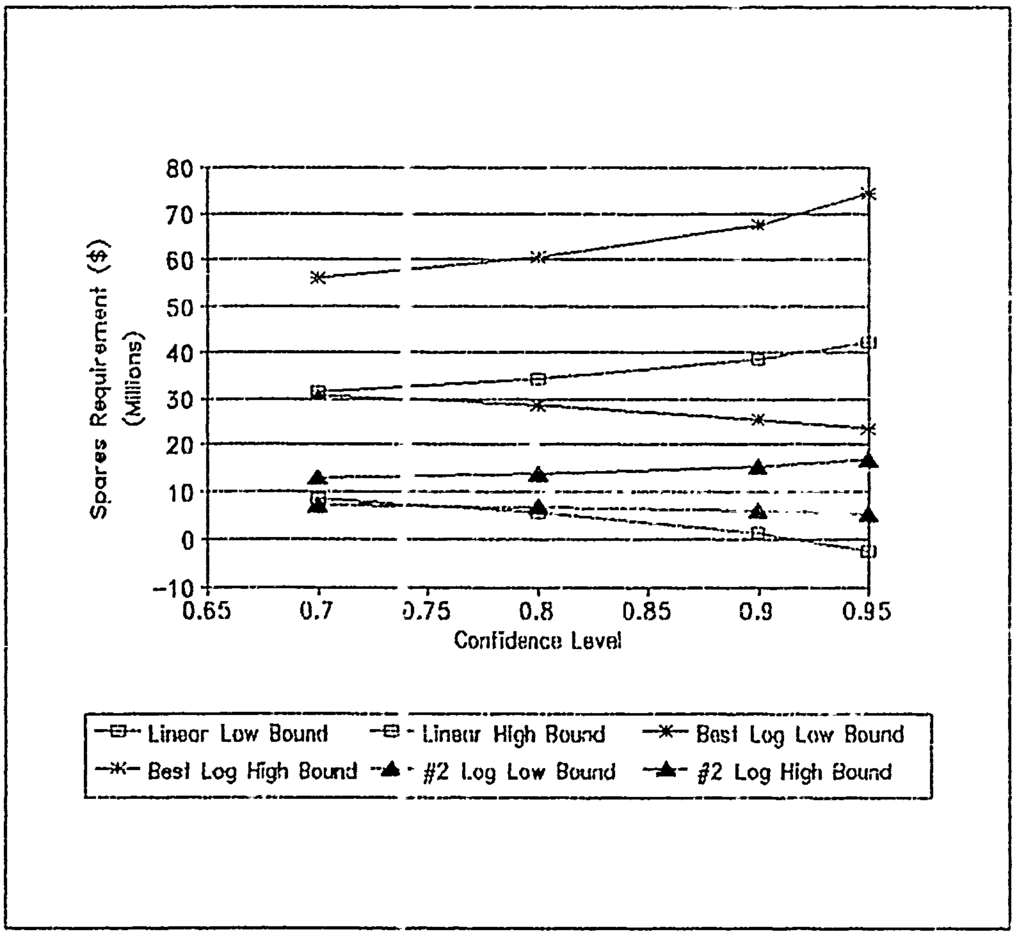

Figure 7. Model Prediction Interval Bounds Comparison

model bounds are also plotted. While the widths of the best log-log model and the linear model appear to be approximately the same, the intervals for the log-log model

occur at a much higher predicted val ıe of Y. A plus or minus $12.8 million bound for an estimate ›f $41.6 million is much more accurate (percentage wise) than a plus or minus $11.6 million bound for an estimate of $19.9 million.

Residual Plots. The same :hree forms of residual plots used in the previous analysis were also used on this log-log models. The model performed essentially the same as first log-log model. Once again, al of the standard residual plots appeared to show rand‹ mly scattered datapoints. Neitherthe of the two additional residual plot forms identified the need for a variable transformation. The data dispersion was a little tighter for this model however.

Outliers. The best log-lo‹; transformation still possessed an outlier problem. Seventeen of the eighty datapoints used in this model were identified as outliers with respect to Y by their studentized residual values. The MDS represented in these outliers included the F-15A, F-15B, F-4D, F-4E, A-7D, A-7K, B-52G, B-52H, C-5A, C-130B, C-130E, and FB-111A. None of the datapoints were outliers with respect to X according to the leverage values.

Once again, the number of outliers which were influential was high according to the Dfbeta test. Fourteen different datapoints were influentia out'iers for one variable or another, including F-15A F-15B, F-4E, A-7K, C-5A, C-130B, and FB-111A datapoints. The Dfits test indicated that only four datapoints including one each of

the F-4E, A-7K, C-5A, and C-130B datapoints) were influential outliers with respect to Y. Once again, no action was taken to alleviate the outlier condition.

Multicollinearity. Neither the tolerance values or the COLLINOINT condition values indicated the presence of significant multicollinearity in this model. The highest condition number was only 4.3115, compared to 8.19456 for the last model. The lowest tolerance value was .19756894. This is a significant reduction in the level of multicollinearity within the model.

Heteroscedasticity. The "datapoint residual versus predicted condemnations plot" did not suggest the presence of heteroscedasticity in this model. The scatter pattern maintained a fairly constant width across the data.

Model Predictive Capability. Table 13 shows how well this log-log transformation model performed in predicting costs for the validation data set (see Appendix E). The SAS provided estimates were multiplied by a bias adjustment factor of 1.042 to arrive at the estimates in Table 13. The average absolute percent error among the fourteen estimates was 27 percent, compared to 30.6 percent for the first log-log model. The model provides no "negative" cost estimates and the largest percentage error was 77 percent (for the A-10A), compared to 116% for the same datapoint in the first log-log model. The largest absolute error was $13,477,655 (for the C-5A) compared to

$25,89^.293 for the same datapoint i: the first log-log model.

TABLE 13

Best Log-Log Transformation Model V..lidation Test Results

MDS	ACTUAL CONDEMN COSTS	Be: t Log-Log ESTIMATE	Estimate Divided by ACTUAL
F16A	27,537,555	46,493,354	1.68
F4D	24,151,890	18,820,898	0.78
F4E	24,254,355	24,178,775	1.00
A7D	20,075,237	12,534,068	0.62
A7K	1,560,822	1,518,977	0.97
A10A	12,012,017	21,269,329	1.77
F111D	14,831,043	11,966,556	0.81
B52G	43,909,467	42,115,435	0.96
B52H	20,415,995	27,415,449	1.34
C5A	71,036,363	57,558,708	0.81
C130B	4,698,837	3,149,006	0.67
C130E	18,837,210	12,688,688	0.67
C141B	51,264,650	43,537,881	0.85
FB111A	13,471,819	11,701,858	0.87

<u>Model Sensitivity</u>. Table 14 presents the results of the model sensitivity test. For :ach cost driver, the

Table 14

Best Log-Log Transformation Model Sensitivity Test

<u>Variable</u>	Delta Y due to <u>increase in X</u>	Delta Y due to <u>decrease in X</u>
ACNUM	+.20	-.20
THRUST	+.15	-.15
TOEMPWT	+.58	-.43
FLYCOST	+.13	-.14

impact of a plus or minus twenty percent change in X (the cost driver value) is presented.

Like the first log-log model, this model is relatively insensitive to changes in all the cost drivers except one "the ratio of maximum takeoff weight to maximum empty weight" (TOEMPWT). A twenty percent increase in this variable results in a 58 percent increase in the cost estimate (compared to 76 percent for the first log-log model).

Small Database Performance. The condensed database test provided mixed results for this model. Using this database, the model's R^2 went up from 92.73 percent to 95.36 percent. Its Root MSE dropped from 28.64 percent to 26.38 percent. Reducing the database size resulted in a large drop in the model's F-Value. It fell from 239.074 to 56.555. The small improvements were not considered significant enough to pursue further analysis using the small database.

Demand Volatility Analysis

This section is divided into two subsections, the first section presenting the results of a replenishment spares CER and the second section looking at spreadsheet generated demand volatility factors.

Replenishment Spares CER. The ultimate goal of producing the condemnation CERs described in the preceding text was to take the estimates generated by these models and

use them to predict annual replenishment spares costs. As discussed in Chapter II, this type of approach is currently included in the HQ AFLC/FMC's Logistics Support Cost Model (LSC) [the LSC model, however, is an accounting type model as opposed to a CER]. An attempt was made to improve upon the accuracy of the demand volatility factor used in the LSC model to convert condemnation costs to replenishment spares costs. The following text presents the results of this effort.

A SIV replenishment spares model was created with SAS using annual MD condemnation costs as the sole cost driver. Appendix G provides the condemnations cost database and replenishment spares requirements database used in development of the SIV. The tables in this appendix also include the mission design (MD) and fiscal year associated with each datapoint. The arithmetic expression of this model is expressed in the following equation:

$$REPLEN = -10,613,130 + 3.75853(CONDEMN) \qquad (11)$$

where

REPLEN = annual replenishment spares requirement ($)

CONDEMN = annual condemnations cost ($)

This model has the same problem found in the linear and arithmetic transformation condemnation CERs--it has a large negative intercept and therefore can result in negative cost estimates. This model also has poor statistics, as one can see in the ANOVA table provided below.

The "condemnations cost" variable has the correct parameter estimate sign and is a significant cost driver (P-Value of .0001). The model's F-Value (129.849) is also greater than that seen in the first two models; but everything else goes down hill from there. The R^2 value (59.06) suggests that there are other sources of error not captured in this model. This statistic is well below the 80 percent acceptance criterion stated at the end of Chapter III. The C.V. (58.46779) tells one that this model is not a very reliable predicter of annual replenishment spares requirements. This is confirmed in Figure 8, which presents the SAS 95% prediction intervals for this model. The interval width is extremely large and still some datapoints fall outside the bounds.

Table 15

Replenishment Spares CER Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	1.6559149E18	1.6559149E18	129.849	0.0001
Error	90	1.1477359E18	1.2752621E16		
C Total	91	2.8036508E18			

Root MSE	112927504.960	R-square	0.5906
Dep Mean	193144805.913	Adj R-sq	0.5861
C.V.	58.46779		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob>¦T¦
INTERCEP	1	-10613130	21409126.648	-0.496	0.6213
CONDEMN	1	3.758530	0.32983652	11.395	0.0001

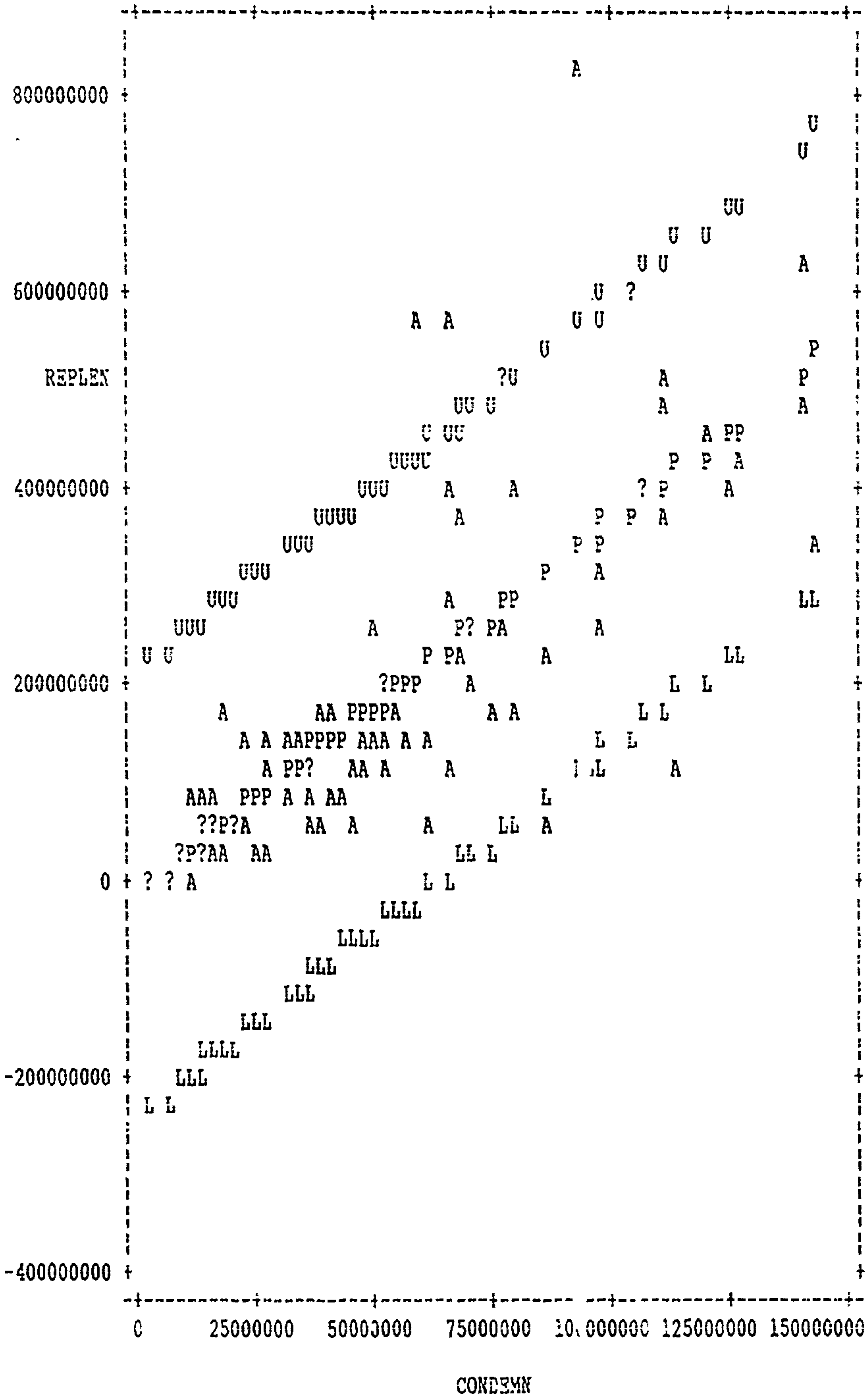

Figure 8. Replenishment Spares CER Prediction Intervals

The model's database also has an abundance of outliers, as seen in the preceding models. Twelve out of 92 datapoints are identified as being outliers with respect to Y and sixpoints are outliers with respect to X. Of these numbers, eight datapoints were tested (Dffits test) as being influential outliers with respect to Y. Six of these eight datapoints and one additional one were also identified as being influential outliers by the Dfbetas test. The Cook's D test did not identify any influential outliers. Once again, no action was taken to adjust the database.

Although the statistics of this model are not very impressive, they do provide one with a sense of how accurate one can expect to be in using the model. The analysis supporting the demand volatility factor used in the LSC model did not provide such statistics.

An additional SAS model was created with the Y-intercept restricted to a value of zero. This action flattened the slope found in the previous model so that one doesn't obtain "negative" estimates. The slope for this model (3.621965) is the value one would use as the demand volatility factor. The ANOVA statistical measurements are no longer meaningful for this model because of the restriction placed upon the model. The demand volatility factor from this model, 3.621965, is significantly larger than the 2.15 value used in the LSC model.

Demand Volatility Analysis. In addition to the SAS generated SIV model described above, demand volatility

factors were developed by comparing MD annual condemnation costs with the annual replenishment spares requirements developed for these MDs two years earlier. Table 16 provides the results of this analysis. The missing demand volatility factors in the T-37 and T-38 data sets are due to holes in the replenishment spares requirements data set. The one missing demand volatility factor in the FB-111 data set is due to the fact that this MD is being converted to another F-111 MDS (Rosenthal, 1991). The factor was abnormally high and it was felt that this was due to the start of the conversion process.

In addition to the individual demand volatility factors, averages are provided both by FY and within the MDs. In fact, two different averages are provided. The first is the average of all the individual demand volatility factors by category (FY and MD). The second average is based upon the raw data behind the demand volatility factors (i.e., rather than just averaging the factors, the total replenishment spares requirements are divided by the total condemnation costs). The first average give equal weight to each of the individual factors, regardless of the MD's relative contribution to total costs. The raw data average gives more weight to high cost items.

Additionally, Table 16 includes the results of a simple trend analysis. If the last three datapoints within a particular MD data set were either lower or higher than the

Table 16

Demand Volatility Analysis

MD	82/84	83/85	84/86	85/87	86/88	87/89	88/90	Factor AVG	Raw Data AVG	TREND
	Replen. Spares FY/ Condemnations FY									
A7	9.01	6.43	2.55	2.57	1.10	1.27	1.70	3.52	3.32	DWN
A10	9.63	9.75	6.14	4.40	2.42	4.21	2.39	5.56	5.39	DWN
B52	5.34	8.70	3.29	3.25	3.08	1.04	0.79	3.64	3.54	DWN
FB111	3.58	5.16	2.03	1.51	1.21	2.38		2.64	2.70	N/A
F111	6.54	6.19	2.35	2.68	2.26	4.23	3.13	3.91	3.76	N/A
C5	9.73	2.76	2.57	0.99	3.01	4.08	4.01	3.88	3.93	N/A
C130	3.61	2.51	2.94	2.96	3.30	1.77	1.46	2.65	2.67	N/A
C135	2.46	2.66	1.12	2.75	3.97	1.88	2.62	2.49	2.29	N/A
C141	3.04	4.19	2.57	2.04	1.27	2.40	1.47	2.43	2.45	DWN
F4	5.13	5.96	3.73	2.09	1.88	1.83	1.31	3.13	3.51	DWN
F15	8.77	4.46	3.89	3.34	3.14	4.51	3.51	4.52	4.35	DWN
F16	5.15	3.38	2.76	5.69	3.71	3.31	4.26	4.03	3.99	N/A
T37					3.87	1.10	0.45	1.81	1.42	N/A
T38	5.18	4.83	4.09		1.41	0.92	1.89	3.05	3.24	DWN
Annual Avg	5.94	5.15	3.08	2.86	2.54	2.49	2.23			DWN
Annual Raw Data Avg	5.79	4.79	2.88	3.09	2.80	2.89	2.70			DWN

data set average, a downward (DWN) or upward (UP) trend was identified.

Although numerous individual demand volatility factors were less than the factor (2.15) used in the LSC model, only the T-37 (with only three factors in the data set) had an MD average which was less. In fact, many of the factor averages were substancially higher than 2.15. Looking at the FY averages shows that none were less than the current LSC factor. The average demand volatility factor for all MDs across all the FYs was 3.46. The raw data average was just a little higher--3.56. Again, this value is substancially higher than the current LSC factor.

When one looks at the trends in the MD factor data sets, however, one sees that half of the MDs have downward trends and none exhibit upward trends. The FY averages confirm this. The annual average demand volatility factors steadily decrease each year. The annual raw data averages do not exhibit a steady decrease, but the trend is definitely downward. The 2.15 factor used in the LSC model comes much closer to the averages experienced over the last few FYs.

The overall downward trend in the factor averages is consistent with the tightening of DoD budget purse strings seen in recent years. The first few years of the analysis database included the "Reagan build-up years." A part of Ronald Reagan's campaign strategy had been to suggest that, under President Carter, the DoD had become a hollow force,

ill-equiped to adequately protect the nation. Funding was not an issue in these years and therefore the replenishment spares requirements were much higher. The abundance of funding, however, was not sustained across the entire analysis database. The lower factor averages in the latter years of the analysis may be due, at least in part, to this fact.

Besides looking for trends in the factor averages, the individual factors were also evaluated to see if they appeared to fall into groupings by aircraft mission (e.g., fighter, bomber, etc.). There was too much variability within the different mission categories and insufficient sample size to draw conclusive results. It was interesting to note, however, that some of the high cost MDs' averages were consistently higher than the current LSC factor. The F-16 and F-15 factors, in particular, have consistently been closer to four than to 2.15.

While no mission-unique demand volatility factors are suggested from this analysis, it is clear that a single factor, used over a number of years for all aircraft, will introduce a significant amount of error to one's estimate.

V. Summary and Recommendations

Introduction

This Chapter summarizes the results of the annual condemnations cost model development and demand volatility analysis. Recommendations for use of the models developed and for further study are also provided.

Summary

The major objective of this thesis was to develop a parametric model for estimating annual replenishment spares costs based upon aircraft physical and performance characteristics. The methodology for achieving this objective was divided into two parts. First, a CER for estimating annual condemnation costs was developed and then the relationship between condemnation costs and replenishment spares requirements was evaluated. The analysis of this relationship was further divided into two steps: 1) a SIV model for estimating replenishment spares costs was developed using annual condemnations as the sole cost driver; and 2) annual replenishment spares requirements (by MD) were compared to annual condemnation costs to arrive at factors known as "demand volatility" or "churn" factors.

Four condemnations CERs were evaluated in the text. The best linear and arithmetic transformation models failed to produce statistically acceptable results. The two best log-log transformation models provided significantly

improved results; but still their predictive accuracy is questionable. While the study showed that performance and physical characteristics could be used to produce statistically significant models, there was too much variability in the data (as evidenced by the number of outliers) to achieve desirable model prediction intervals.

The demand volatility factor analysis suggests that one factor (for all aircraft and all fiscal years) does not adequately represent the changing conditions which impact the relationship of replenishment spares requirements to condemnation costs. A downward trend in the factor averages was observed across the data--indicating the need for continuing trend analysis to update any factor used. No mission-unique factors were suggested due to variability in the factors and inadequate mission-unique sample sizes.

<u>Recommendations for Use</u>. The first two models analyzed for this thesis (linear and arithmetic transformation models) are not recommended for use due to their poor statistical performance. The two log-log transformation models are viable cost models for predicting annual condemnation costs. Because neither model was blessed with small prediction intervals, however, it is recommended that they are used for comparison purposes with other estimating approaches and not as the primary estimating tool.

The replenishment spares CER had even poorer statistics than the linear and arithmetic transformation condemnation CERs and therefore isn't recommended for use.

The overall demand volatility average was significantly higher than that currently used by HQ AFLC/FMC in their Logistics Support Cost Model. However, there is a downward trend in the data and if one were to average the factors over the last three years in the data set, the factors would not be nearly as far apart. Given the number of adjustments made to the replenishment spares database so that it could be compared with the condemnation costs database (see Chapter III), it would probably only be vanity that suggests this thesis's factor average is superior to the one currently in use. This point is really mute, however, because the analysis suggests that one factor should not be used for all aircraft and across numerous fiscal years. The MD factor averages are recommended as starting points for developing analogous weapon system demand volatility factors. Because trends were identified in the data, future users should first update the database with the latest data available before using the MD factor averages.

Recommendations for Future Study. There are several areas related to this research which would benefit from additional study. The whole topic of demand volatility is a relatively unexplored domain with very little research conducted and even less written down. Though one would think that condemnations should be the major driver of

replenishment spares requirements, what little research that has been conducted to date indicates otherwise.

If the number of replenishment spares required each year truly exceeds the condemnations by the ratios of two to one and greater, one must wonder what happens to all the spares. With aircraft modifications occurring continuously, perhaps a large number of spares become obsolete. Whether data exists for this kind of study is unknown; but the research would be enlightening.

This demand volatility factor analysis examined whether or not the factors tended to group by mission category. Additional study should be conducted to determine if the work unit code unique factors could be developed. For example, avionics spares may have a different factor average than the airframe spares.

If a suitable database is discovered or developed, the same research conducted in this thesis for replenishment spares can be conducted for initial spares.

Appendix A: Definition of Terms

Unless specified otherwise, the following definitions are taken from the AFLC Cost Analysis Handbook (TASC,1989):

Additives - Initial spare "additives" are special stock level requirements over and above those determined by the standard AFLC Form 614 process. Replenishment spares additives are, as the name implies, requirements which are calculated separately from the D041 calculations and added manually into the D041 system (Rosenthal, 1991).

Analogy Based Estimating - method of cost estimating based upon adjusting the actual cost of a similar existing system for "complexity, technical, or physical differences," between it and the new system for which the estimate is being derived (Ch 14, 27).

Availability - A measure of the degree to which an item is in an operable and committable state at the start of a mission when the mission is called for at an unknown (random) time. (Ch 5, 31)

Base Repair Cycle Time (BRCT) *Pipeline* - The average number of spares resident in the base level repair process at any given point in time (Dement, 1990:Appen 1, sec 2.1.2).

Condemnations - When the cost to repair a spare exceeds 75% of the cost to purchase a new spare, the item is "condemned" (Novak, 1991). Condemnation spares, therefore, are those spares purchased to replace the condemned spares.

Cost Estimating Relationship (CER) - a mathematical relationship that relates one variable, usually cost (called the dependent variable), to one or more other cost drivers (called the independent variables). (Ch 10, 3)

Cost Drivers - "Those [independent] variables that exhibit some systematic relationship with cost" (Ch 10, 3).

Demand Based Sparing - A category of inventory control/cost estimating models which base their stockage recommendations upon the probability of meeting the demand for a spare part out of available stock (AFLCP 57-13, 1987:10).

Demand Volatility - Condemnation spares are only a subset of the total replenishment spares requirement. The difference between these two requirements is attributed to "demand volatility" (as known as "churn"). The causes of demand volatility include: 1) replenishment spares funds are used to purchase pipeline spares when initial spares funds are inadequate, 2) changes in flying hour program, parts utilization rates and maintenance factors, and 3) additive requirements (Novak, 1991).

Depot Repair Cycle Time (DRCT) *Pipeline* - The average number of spares in the depot level repair process which were originally generated at the base level (Dement, 1990:Appen 1, sec 2.2.1).

Engineering Cost Estimate - An approach to cost estimating that "encompasses a detailed 'build-up' of labor hours, material costs, and overhaul at very finite subindentures of the program/activity/item for which cost is to be estimated" (Ch 14, 28).

Flyaway Costs - Non-recurring plus recurring costs for airframe, propulsion and avionics, program management, test and evaluation, [and] allowances for engineering changes. (Levine and Horowitz, 1989:5)

Initial Spares - Repairable components which support newly fielded end items (or principal items) for the entire production run of the aircraft (Rexroad, Tillia, and Tritle, 1990:21).

Independent Cost Estimate (ICE) - A cost estimate performed by an "honest broker" with no ties to the program office. It is used as a check for the reasonableness of the program cost estimate (Ch 14, 8).

Initial Spare Support List (ISSL) - ISSLs include those provisioned items which the equipment specialist and the using command agree should be stocked and on-hand for support of operations and maintenance at the operational location when the first items become operational. (Reynolds, 1989:15)

Job Routed (JR)/Non-JR Repair Cycle Time Pipeline and Depot Overhaul Stock - spares required to cover "programmed depot maintenance and component overhaul" (Dement, 1990:Appen 1, sec 2.2.2).

Life Cycle Cost (LCC) - The total cost to the Government of acquisition and ownership of the system over its full life. It includes the cost of

development, acquisition, operation, support, and where applicable, disposal. (Ch 5, 33)

Line Replaceable Unit (LRU) - An aircraft is composed of major subassemblies such as the avionics system. These systems are, in turn, composed of final assemblies or components known as LRUs (AFLCP 57-13, 1987:3).

Maintainability - A system or component characteristic which "refers to the ease with which a given component/system can be maintained" (Ch 5, 18).

Mean Time Between Demand (MTBD) - A derivative of the mean time between failure (MTBF) which has been modified to account for demand drivers not included in the MTBF. For example, the MTBF does not include component failures which are beyond the contractor's responsibility such as operator error and mishandling (Reynolds, 1989:81-82).

Mean Time Between Failure (MTBF) - For a particular interval, the total functional life of a population of an item divided by the total number of failures within the population. (Ch 5, 33)

Most Probable Cost (MPC) - An estimate used during source selection to check the reasonableness of a bidder's cost proposals (Ch 14, 9).

Obligation - As used in the Air Force program control community, funds are said to be "obligated" at that point in time when the contractual agreement between the Air Force and contractor is posted into the official accounting and finance records. "Obligations" are separate from "commitments" and "expenditures." The former takes place when a purchase request or other authorized commitment document is signed by the accounting & finance certifying official and the latter takes place when the Air Force pays the Contractor.

Operations and Support (O&S) *Costs* - Fixed and variable costs of personnel, material, facilities, and other items needed largely for the peacetime operation, maintenance, and support of a system during activation, steady state operation, and disposal. (Ch 17, 3)

Order and Shipping Time (OST) *Pipeline* - The number of spares required to cover the time to order and ship spares to the base from the depot whenever components are sent to the depot for repair or are condemned [see "condemnations" above] at the base. It is based on the average shipping and handling times and average supply

demand rates at the base level. (Dement, 1990:Append 1, sec 2.1.1)

Procurement Lead-time - The sum of the administrative and production lead times. Administrative lead time (ALT) is "the period of time, in whole months, from the start of IM [item manager] preparation of purchase request/military interdepartmental purchase request (PR/MIPR) to date of contract award" (AFLCR 57-4, 1983:Ch 1, 5). Production lead time (PLT) is "the time between award of the contract or purchase order and resultant first significant delivery quantity" (AFLCR 57-4, 1983:Ch 1, 6).

Procurement Lead-time Spares - spares which are purchased to ensure adequate stock during the administrative and production lead-times for items" (Dement, 1990:Append 1, sec 2.3.2).

Program Cost Estimate (PCE) - The "program manager's official estimate of the financial resources required to competently conduct the program contained in its Program Management Directive (PMD)" (Ch 14, 8).

Provisioning - The process of determining and acquiring the range and quantity (depth) of spares and repair parts, and support and test equipment required to operate and maintain an end item of material for an initial period of service. (Ch 5, 34)

Provisioning Technical Documentation - A "generic term for all the provisioning data developed by the contractor, including listings, drawings, diagrams, schematics, etc." (Reynolds, 1989:10).

Recoverable Spares - "Repairable parts, assemblies, components, etc. used in the repair of higher level assemblies" (Reynolds, 1989:49).

Readiness Based Sparing - A category of inventory control/cost estimating models which base their stockage recommendations upon maintaining sufficient spares to ensure aircraft availability goals are met. The key difference between this approach and demand based sparing is that the demand for a spare does not necessarily imply that an aircraft cannot perform its mission (Horner, 1991).

Reliability - The probability that the system will satisfy the need for which it was intended in an acceptable manner, for a given period of time, when deployed and used under a given set of operating conditions. . . . Satisfactory performance describes

the level at which the item/system must perform; performance below this level is then considered "failure" even though the specific part/component has not broken or reached a zero performance level. (Ch 5, 16)

Repair Parts - "Consumable non-repairable parts used to repair higher level assemblies" (Reynolds, 1989:49).

Replenishment Spares - Repairable components, assemblies, or subassemblies required to resupply initial stockage or increased stockage for reasons other than support of newly fielded end items. Replenishment would include additional stockage due to increases such as usage, readiness initiatives, and redeployment of end items. (Ch 17, 40)

Safety Level - The quantity of spares held at both the base and depot repair facilities to account for fluctuations in the pipeline requirements (Dement, 1990:Appen 1, sec 2.1.3 & 2.2.3).

Shop Replaceable Unit (SRU) - The subcomponents which together compose a line replaceable unit (LRU) are known as SRUs (AFLCP 57-13, 1987:3).

Should Cost Estimate (SCE) - A cost estimate developed for individual contracts as a basis for the Government's negotiation objective (Ch 14, 9).

Single Best Estimate (SBE) - A cost estimate which results when the independent cost estimate and program cost estimate processes are combined as one. Both program office and staff cost analysts combine to form a joint estimating team in developing the SBE (Ch 14, 9).

Source, Maintenance, and Recoverability (SMR) *Code* - A code assigned to every item (both recoverable spares and repair parts) identified in the provisioning technical documentation. The code "indicates the method of support [i.e., base, intermediate, or depot repair], authorized maintenance actions [e.g., repair, reconditioning, etc.], and appropriate disposal authority for each item" (Reynolds, 1989:12-13).

Appendix B: Recoverable Spares Cost Estimating Background

Introduction

The purpose of this appendix is to provide additional background information for those readers new to the field of aircraft recoverable spares cost estimating. The text begins with definitions for key terms. Following this are descriptions of the current methodologies for developing both spares budgets and buy requirements. These descriptions are divided into separate subsections devoted to the two major classes of recoverable spares--initial and replenishment--beginning with the former class. After this, a discussion of how spares cost estimating relates to the life cycle phase of the aircraft is provided. Related subtopics in this section are: 1) the maintenance plan development, 2) the various methodologies for cost estimating, and 3) the different reasons for cost estimates. Finally, the appendix concludes with an analysis of the different sources of data relating to recoverable spares evaluated for this thesis.

Key Terms

Before proceeding any further in the text it is important that several key terms be defined. First, the two major classes of recoverable spares (those which can be repaired when broken) are defined as follows:

> *Initial Spares* - Repairable components which support newly fielded end items (or principal items) for the entire production run of the aircraft. The budget will support stockage at all levels including the pipeline Initial spares will also include whole spare engines. (Rexroad, Tillia, and Tritle, 1990:21)

> *Replenishment Spares* - Repairable components, assemblies, or subassemblies required to resupply initial stockage or increased stockage for reasons other than support of newly fielded end items. Replenishment would include additional stockage due to increases such as usage, readiness initiatives, and redeployment of end items. (TASC, 1989:Ch 17, 40)

These definitions requires some clarification and further definition. Before 1985, initial spares would only cover newly fielded aircraft for an average of two years. After this point, all spares were considered replenishment spares, even if the actual production line for the new aircraft continued on for many years. Under the new definition of initial spares, *each production lot* is covered for a period of approximately two years before transitioning to replenishment spares. If the production line provides (for example) ten lots of aircraft over a ten year period, each lot is covered by initial spares for its own two year period (Rexroad, Tillia, and Tritle, 1990:21). There were aircraft whose production line began before the new definition and continued on afterwards. For these aircraft, if the two year initial spares coverage period had already ended and replenishment spares were being used when the definition changed, they continued to use replenishment spares funds to cover all future spares requirements. In other words, these aircraft were "grandfathered" under the

old definition. Those aircraft still in the midst of their two year initial spares coverage adopted the new definition and thus future production lots received their own initial spares coverage period (Rosenthal, 1991; Neuhart, 1991).

The initial spares definition mentions that this class covers the "pipeline". Because recoverable spares can, by definition, be repaired there are always a number of spares in the process of being repaired or in transit to or from the repair facilities. The "pipeline" is divided into several pieces. The *Order and Shipping Time (OST) Pipeline* is

> the time to order and ship spares to the base from the depot whenever components are sent to the depot for repair or are condemned [see "condemnation spares" below] at the base. It is based on the average shipping and handling times and average supply demand rates at the base level. (Dement, 1990:Append 1, sec 2.1.1)

The *Base Repair Cycle Time (BRCT) Pipeline* is "the average number of spares resident in the base level repair process at any given point in time" (Dement, 1990:Appen 1, sec 2.1.2). The *Depot Repair Cycle Time (DRCT) Pipeline* is "the average number of spares in the depot level repair process which were originally generated at the base level" (Dement, 1990:Appen 1, sec 2.2.1). The *Job Routed (JR)/Non-JR Repair Cycle Time Pipeline* and *Depot Overhaul Stock* provide spares to cover "programmed depot maintenance and component overhaul" (Dement, 1990:Appen 1, sec 2.2.2). An analogy for this last subset of initial spares is when an auto mechanic is performing a scheduled maintenance check on one's car and

he recommends that a few parts be replaced. These parts have not yet failed; but it isn't worth trying to prolong their life when their failure may result in greater, costlier damage to the vehicle.

Also included in initial spares requirements are safety level stock, procurement lead-time, additives, and condemnation spares. The base and depot safety levels provide additional spares to account for fluctuations in the pipeline requirements (Dement, 1990:Appen 1, sec 2.1.3 & 2.2.3). AFLCR 57-27, Initial Requirements Determination, does not provide for initial spares "safety stock" by name as seen in the replenishment spares regulations. It does, however, allow budgeting for the purchase of initial spares to cover the lead-time (the period of time from obligation of funds to spares delivery) plus an additional three month supply (AFLC 57-27, 1986:60; Rosenthal, 1991). This standard three month period is not as sophisticated as the marginal analysis techniques used to develop replenishment spares safety level (Rosenthal, 1991) but it serves the same purpose. "Procurement lead-time spares are purchased to ensure adequate stock during the administrative and production lead-times for items" (Dement, 1990:Append 1, sec 2.3.2). Initial spare "additives" are special stock level requirements over and above those determined by the standard AFLC Form 614 process. When the cost to repair a spare exceeds 75% of the cost to purchase a new spare, the item is

"condemned" (Novak, 1991). Condemnation spares, therefore, are those spares purchased to replace the condemned spares.

The definition for replenishment spares implies that this class of spares coverage basically picks up when initial spares coverage ends. In reality, the break between the categories is not as clean as the definitions imply. The term "replenishment" suggests maintaining a previously established level of spares. Condemnation spares do fulfill this function as one of the major elements of replenishment spares; but they are only a part of the total replenishment spares requirement. There have been (and continue to be) situations where the initial spares estimates were inadequate and pipeline requirements were filled with replenishment spares funding (Rosenthal, 1991). The final major element of replenishment spares are additives. The "Recoverable Consumption Item Requirements System" (D041) computes replenishment spares requirements based upon historical demand. Replenishment spares additives are, as the name implies, requirements which are calculated separately from the D041 calculations and added manually into the D041 system (Rosenthal, 1991). AFLCR 57-4, the governing regulation for D041, provides a list of the numerous additive requirements. Replenishment spares also cover smaller categories of requirements such as safety level and procurement lead-time spares.

Finally, several additional spares requirements such as negotiated base stock levels, forward supply support levels,

war readiness material kits, depot floating stock, insurance, and foreign military sales are included in the total recoverable spares requirement. These categories of spares represent special requirements that are tracked separately. As such, they are not included in the scope of this discussion. One may look to AFLCR 57-4, Recoverable Consumption Item Requirements System (D041) for additional details on these requirements.

Additional terms requiring definition at this time include:

Availability - A measure of the degree to which an item is in an operable and committable state at the start of a mission when the mission is called for at an unknown (random) time. (TASC, 1989:Ch 5, 31)

Flyaway Costs - Non-recurring plus recurring costs for airframe, propulsion and avionics, program management, test and evaluation, [and] allowances for engineering changes. (Levine and Horowitz, 1989:5)

Provisioning - The process of determining and acquiring the range and quantity (depth) of spares and repair parts, and support and test equipment required to operate and maintain an end item of material for an initial period of service. (TASC, 1989:Ch 5, 34)

Initial Spares Budget Development

Historically, the agency responsible for initial spares budget preparation, HQ AFLC/FMBSR, has used a factor based approach to developing their initial spares requirements (with the exception of whole engine spares). This has primarily involved multiplying aircraft flyaway cost by a spares "factor" [additional factors are applied against training and peculiar support equipment]. These factors are

sometimes adjusted based on the expert opinion of the budget manager given any input from other sources such as the Air Logistics Centers (ALCs) or System Program Offices (SPOs) (Neuhart, 1991; Rexroad, Tillia, and Tritle, 1990:1). The underlying logic of this methodology is limited to the assumption that the greater a weapon system's flyaway cost, the more expensive its spares will be. It continues to be used because: 1) data inputs required for other models are either not available or very hard to come by, and 2) it is easy to apply.

There are two changes to this historical perspective. First, HQ AFLC/FMBSR has given most of its responsibility for budget preparation to the ALCs [they still budget for common support equipment and whole spares engines are handled separately]. The FY 92/93 Budget Estimate Submission (BES), dated September 1990, was the first ALC input (Neuhart, 1991). Second, the factor based approach to developing initial spares budgetary requirements has been criticized for its lack of insight into the underlying causal relationships driving the estimates (Dement, 1990:Sec 1; Rexroad, Tillia, and Tritle, 1990:1) and efforts are underway to develop a new methodology.

For a while, demand based approaches similar to those used in the initial spares provisioning process were considered the likeliest candidates to replace the factor based approach. This mentality is seen in a coordinated message from SAF/FMC, SAF/AQK, SAF/AQX, and HQ USAF/LEX,

dated 2 October 1990, which stated that the Air Force Cost Analysis Improvement Group (AFCAIG) preferred the use of "valid, demand based models for calculating initial and condemnation spares for POE's [Program Office Estimates] and ICA's [Independent Cost Estimates] presented to them for Defense Acquisition Board (DAB) milestones" (SAF/FMC, 1990, 2). Demand based approaches such as the Logistics Support Cost (LSC), and ModMETRIC (see Appendix C) are concerned with the probability of meeting the demand for a spare part out of available stock (Alexander, 1990:III-24; AFLCP 57-13, 1987:10). Studies were conducted to evaluate demand based approaches that would fulfill the initial spares budget development role (Dement, 1990; Rexroad, Tillia, and Tritle, 1990); but before an "approved" methodology was arrived at, the emphasis switched from "demand based" to "availability" or "readiness based" approaches.

The use of readiness based sparing (RBS) methodologies is expected to reduce recoverable spares costs (Beckett, 1). While demand based models try to ensure that spares are available upon demand, the RBS models recognize that demand for a spare doesn't necessarily imply that an aircraft must be grounded or can't perform its mission. The RBS methodology, rather than focusing on the demand for individual spare parts, is concerned with maintaining sufficient spares stock to ensure aircraft availability goals are met (Horner, 1991). This theoretically smaller stock results in reduced recoverable spares costs.

According to a HQ USAF/LEYS letter dated 14 November 1990, the Office of the Assistant Secretary of Defense, Production and Logistics (OASD/P&L) was preparing a new regulation to replace DoDI 4140.42, Determination of Requirements for Secondary Item Spare and Repair Parts Through the Demand Period, which will mandate the use of RBS methods (Beckett, 1). HQ AFLC/XRI is currently evaluating the RBS methodology used by the Army and Navy for potential Air Force implementation (Robinson, 1991).

Until a practical alternative methodology is developed to replace the factor based approach, it will probably continue to be relied upon for developing initial spares budgets (as evidenced by the number of ALCs using it for their FY 92/93 BES inputs (Neuhart, 1991)).

Initial Spares Provisioning Requirements Development

Due to the length of the Program Objective Memorandum (POM) process (the long range budget plan), initial spares budget wedges are typically put in place several years before initial spares provisioning actually occurs (Neuhart, 1991). Details of an aircraft's maintenance plan required for initial spares provisioning are not always available when these budgets are being developed (TASC, 1989:Ch 5, 55); therefore, the factor based approach to budgeting discussed above bears little resemblance to the method used for initial spares provisioning. While budgets are submitted for "aircraft" requirements, provisioning takes

place at the individual "parts" leve`. This section will provide an overview of the method used to determine the "range and depth" of initial spares requirements known as the initial spares provisioning (Reynolds, 1989:5). It should be remembered that "provisioning", as defined previously, encompasses more than initial spares; but the scope of this discussion excludes information not pertinent to spares. Unless indicated otherwise, references in this section will come from a 1989 analysis of the Initial Spares Support List (ISSL) process sponsored by the Air Force Logistics Management Center. The analysis team was led by Captain Steve Reynolds. This reference is recommended for readers who are interested in an in depth analysis of the entire provisioning process.

Provisioning Methods. Activities which take place during provisioning include

> the assigning of Source, Maintenance, and Recoverability codes; assignment and review of the various provisioning factors which quantify projected usage requirements; assignment of Item Management codes; assignment of Federal Supply Classes; etc." (7).

Before explaining these activities in more detail, the three methods used for provisioning will be described in the following order: 1) the Provisioning Conference; 2) the Resident Provisioning Team; and 3) the Depot Committee.

The Provisioning Conference is the most commonly used provisioning method. Participants may include the prime contractor, the Systems Program Manager (SPM)/End Article

Item Manager (EAIM), representatives from the using command and the Defense Logistics Agency (DLA), and the Air Logistics Center equipment specialists. This team meets on a temporary basis at a time and place which is mutually agreed upon to accomplish the provisioning function (7).

Major weapon systems may make use of the Resident Provisioning Team approach. In this method, the provisioning team is a small group of specially qualified personnel who are assigned on a permanent basis to the contractor's facility. The objective of this approach is

> to reduce the time required to furnish the contractor with spare and repair parts orders, to achieve a greater degree of understanding and cooperation between the contractor and the Air Force, and to ensure a greater degree of compliance with provisioning requirements by the contractor. (9)

The final provisioning approach is reserved for those cases where the "system or end item is not overly complex or the number of items involved is not too great" (10). This smaller scale version of the Provisioning Conference takes place at a Depot and is called the Depot Committee.

Provisioning Technical Documentation (PTD). PTD is a "generic term for all the provisioning data developed by the contractor, including listings, drawings, diagrams, schematics, etc." (10). The PTD is the basis for the provisioning team's decisions regarding the range and depth of required spares. The System Program Office (SPO) is the agency responsible for including PTD requirements in their

systems acquisition contract. PTD is entered into and maintained on the AFLC Provisioning System (D220) (10).

Provisioning Activities. As previously stated, provisioning activities include assigning codes and factors which "identify (1) which items will be required for systems support, (2) how many items will be required, and (3) how those items will be managed in the inventory" (12).

A *Source, Maintenance, and Recoverability* (SMR) code is assigned to every item (both recoverable spares and consumable repair parts) identified in the PTD. This code "indicates the method of support [i.e., base, intermediate, or depot repair], authorized maintenance actions [e.g., repair, reconditioning, etc.], and appropriate disposal authority for each item" (12-13). It is this code, assigned by the ALC equipment specialist (12), which fulfills the function of identifying the range of recoverable spares required.

Other codes include the *Item Management Code* (IMC) which assigns management responsibility for each item and the *Material Management Aggregation Code* (MMAC) which groups related hardware for management purposes that might otherwise be separately managed (13 & 15). The *Federal Supply Class* identifies which commodity group the item belongs to (15).

A subset of the recoverable spares identified by the SMR code are placed on the *Initial Spare Support List* (ISSL).

> ISSLs include those provisioned items which the equipment specialist and the using command agree should be stocked and on-hand for support of operations and maintenance at *the operational location* [emphasis added] when the first items become operational. (Reynolds, 1989:15)

The "operational locations" must have a stock quantity of at least one for every spare identified on their ISSL (24).

Identifying the "range" of spares required is only a partial fulfillment of the initial spares provisioning objective. The "depth," or number of spares required must also be computed. AFLCR 57-27, Initial Requirements Determination, is the governing regulation for determining the quantity of new spares (those not already stocklisted). The computations associated with AFLC Form 614, "Recoverable Item Initial Requirements Computation Worksheet," are the "standard" methodology for determining the depth of required spares; but other computerized models may be authorized by AFLC/XRI on an exception basis (20). In fact, according to one source (Dement, 1990:Sec 3), XRII (then MMIE) recommends the use of the Mod-Multi-Echelon Technique for Recoverable Item Control (Mod-METRIC) model. This model, discussed in appendix C, was used on both the F-15 (Huff, 1979) and F-16 (27) fighter aircraft programs.

The AFLC Form 614 computations make use of provisioning factors supplied by the ALC Equipment Specialist (16) and information relating to the aircraft's "operational use"

supplied by the Systems Program Manager (18) to determine the spares requirements.

The provisioning factors are based upon contractor input and the knowledge and experience of the Equipment Specialist. The following factors are used in the process of determining initial spares requirements:

a. Maintenance factor,

b. Overhaul replacement percent,

c. Base condemnation percent,

d. Depot condemnation percent, and

e. Not reparable this station (NRTS) percent (16).

Maintenance Factor. The maintenance factor estimates the rate of demand for a spare part. It is defined as "the estimated average maintenance replacement rate per operating program increment (OPI). The OPI is either considered to be 100 operating hours or 1000 rounds expended, whichever is appropriate" (16).

Overhaul Replacement Percent. The overhaul replacement percent "represents the replacement rate for a spare or repair part in the overhaul of the next higher assembly (NHA)" (17). This estimated percentage includes those items replaced because they have failed and those items replaced because they are deemed to be near failure. This is analogous to an auto mechanic wanting to change one's oil filter--not because it won't last a couple hundred miles more, but because it isn't worth risking the

catastrophic failure of one's engine for the price of a new oil filter.

Base Condemnation Percent. This factor is, as the name implies, the estimate of the percentage of spares which will be condemned at the base repair level (17).

Depot Condemnation Percent. This factor is the estimate of the percentage of spares replaced during depot overhaul which are condemned (18).

Not Repairable This Station (NRTS) Percent. This factor "corresponds to the portion of assets which are authorized intermediate level repair which will have to be returned to the depot for repair action" (18). The causes for this vary but they include inadequate equipment and labor skills and/or insufficient capacity at the intermediate levels (18).

As stated previously, these factors, along with operational program information collected by the System Program Manager on checklists such as the AFLCR 57-27, are then used in computations to determine spares requirements. Figure 9 provides examples of these computations.

The AFLC Form 614 computations have, historically, been a manual process. This process is being automated on a system known as the Initial Requirements Determination (IRD) system. The IRD is currently in system validation test and should be on line by the end of the summer of 1991 (Horner, 1991).

DLM NJR Annual Demand = Average Month Program x 12 x QPEI (for engine O/H or programmed depot maintenance) or QPNHRA (for MISTR items) x Applications % x NJR Program % x NJR Replacement %

DLM JR Annual Demand = Average Month Program x 12 x QPEI or QPNHRA x (1 - NJR Program %) x JR Condemnation % x Application %

Total DLM Annual Demand = DLM NJR Annual Demand + DLM JR Annual Demand

OIM Annual Demand = Average Month Program x 12 x QPEI x OIM Demand Rate x Applications %

Where

DLM = Depot Level Maintenance

NJR = Non-Job Routed

QPEI = Quantity Per End Item

JR = Job Routed

O/H = Overhaul

MISTR = Management of Items Subject to Repair

QPNHRA = Quantity Per Next Higher Recoverable Assembly

OIM = Organizational or Intermediate Maintenance

Figure 9. Example AFLC Form 614 Requirements Computations (AFLCR 57-27, 1986: 5-6)

As previously stated, the AFLC Form 614 process is used to predict requirements for spares which are new to the inventory. These new spares are "assigned National Stock Numbers (NSNs) for purpose of identification and management" (11) and, if AFLC managed, their requirements are entered into the D041 system for determination of replenishment spares requirements. Some spares are acquired from Non-AFLC agencies. These agencies will also stocklist their new spares for managing future Air Force requirements (27).

Initial spares requirements must also be determined for items already in the inventory. For those "existing" items which are AFLC managed, the Item Manager uses the D041 system (used for replenishment spares calculations) to determine any additional quantities required to support the new aircraft (Horner, 1991; Rosenthal, 1991). The Item Manager may use the AFLC Form 614 worksheet to determine requirements for non-AFLC managed existing items and must work with the non-AFLC agencies to determine if they have adequate stocks for these parts (27).

Replenishment Spares Buy Requirements Determination

Unlike initial spares, where the budget process bares little resemblance to the execution (provisioning) process, replenishment spares budget forecasts are based upon the same process (D041 calculations) used to execute the budget. It is appropriate, therefore, to reverse the order of presentation used for initial spares and begin this section

by describing the D041 system used to calculate replenishment spares buy requirements. Unless stated otherwise, references in this section will come from a June 1987 AFLC training program entitled "Introduction to D041 Requirements System" (course # LMMIMO6).

The Recoverable Consumption Item Requirements Computation System (D041) actually serves several functions. In addition to determining buy requirements, D041 computations: 1) assist in managing depot repair requirements, 2) develop Central Secondary Item Stratification (CSIS) lists for spares budget development, 3) determine spares contract termination requirements, 4) report excess requirements for disposal action, and 5) provide for control of distribution of the spares requirements (Ch 1, 5-6).

Figure 10 provides a summary level view of the basic requirements computation process employed by D041. The methodology is similar to that used for initial spares provisioning (AFLCR 57-27) in that factors are developed to predict future requirements. It differs, however, in that the initial spares provisioning factor estimates are typically manually developed by the ALC equipment specialists based upon contractor inputs and their own expertise, while the automated D041 factors can be updated based on historical usage recorded during the initial spares coverage period (an average of two years worth of data). Figure 11 provides examples of the D041 requirements

* USAGE / PAST PROGRAM = FACTOR

* FACTOR x FUTURE PROGRAM = PROJECTED USAGE

* PROJECTED USAGE

+ STOCK LEVELS

+ WAR READINESS MATERIALS

+ ADDITIVE REQUIREMENTS

= GROSS REQUIREMENT

* GROSS REQUIREMENT

- ASSETS (Serviceable assets plus base and depot repairables)

= NET REQUIREMENT

Figure 10. D041 Requirements Determination Methodology (Ch 1, 2 & Ch 7, 1)

computation factors. These factors, developed on past usage, are then applied to the projected future flying programs to predict future spares requirements. Stock level requirements, war readiness material requirements, and additives are added to these predicted levels to arrive at gross requirements. Serviceable assets on hand and those projected to be repaired at base and depot facilities are then subtracted to arrive at the net buy requirement (Ch 1, 1).

* Base Reparable Generations = Base RTS + Base NRTS + Base Condemnations

* Depot Reparable Generations = Job Routed Condemnations + NJR Generations

* Depot O/H Condemnation % = Depot O/H Condemnations / (Depot O/H Condemnations + Depot O/H Repaired)

* Item Past Program = Application Past Program x QPA x Application %

* Usage Element / Past Program = Factor

Where

RTS = Repairable This Station

NRTS = Not Repairable This Station

NJR = Non-Job Routed

O/H = Overhaul

QPA = Quantity Per Application

Figure 11. Example DO41 Requirements Factors
(Ch 7, 1)

The D041 system is actually at the center of numerous other computerized systems that feed data into it. Chapter 10 of AFLCR 57-4 describes these input systems in detail. There are three major categories of input data: 1) programmatic information, 2) historical spares usage data, and 3) inventory assets information. The "Worldwide Stock Balance and Consumption Report" (SB&CR) provided by the D104 system provides two of these categories--usage and assets. Because it is the major data contributor, the data cutoff dates for the quarterly D041 runs are aligned with the SB&CR cutoff dates--30 June, 30 September, 31 December, and 31 March (Ch 2, 2).

Each June D041 cycle contains quarterly spares requirements forecasts for 25 quarters plus a three year lump-sum retention estimate (9 1/4 fiscal years total). As the fiscal year progresses, each passing quarter is dropped from the computations until the following June cycle when another fiscal year's (four quarters) forecast is added. In this way the number of quarters included in the forecast varies from 25 to 22 (and then back to 25) (Ch 7, 7).

For budgeting purposes, separate runs known as the Central Secondary Item Stratification (CSIS) runs are computed. Each June CSIS contains forecasts for the June quarter and the following 12 quarters. The number of quarters forecasted varies for each cycle in the same manner described above (Ch 7, 8).

These automated computations are reviewed by the inventory management and equipment specialists at the ALCs for error correction and validation before they are formalized. The specialists' interface with the D041 system is known as "file maintenance" (Ch 2, 1-2). It is the inventory management specialist who is ultimately responsible for a computation's accuracy and, along with it, the Air Force's support posture for the item (Ch 1, 1).

Replenishment Spares Budget Development

As stated previously, the replenishment spares budget forecasts are based upon the D041 system computations. Near-term budgetary requirements such as the President's Budget (PB) and Budget Estimate Submission (BES) inputs are "scrubbed" versions of the D041 CSIS reports. According to the Repairable Stock Division Program Manager at HQ AFLC, the scrubbing process which he and the ALC specialists perform can involve numerous assorted modifications to the CSIS. Besides corrections for problems such as data entry errors (a few stray zeros can really mess up a forecast), changes are made to accommodate Congressional or Headquarters Air Force direction concerning the size of the budget. In one instance, the Office of the Secretary of Defense (OSD) predicted that moving the replenishment spares budget to a stock fund concept (DMRD 904) would save 10% of the budget and therefore the spares budget was decremented by 10%. In general, the budget is "scrubbed" so that, for

whatever reason, an item's budgetary requirement does not fall drastically out of line with its recent execution experience. For example, it would be politically unacceptable for an item which has experienced an annual usage requirement of one million dollars for five straight years to suddenly require (per D041) a ten million dollar annual budget (Rosenthal, 1991).

Long range budget requirements for the Program Objective Memorandum (POM) are also based on D041 CSIS reports. The Air Logistics Early Requirements Technique (ALERT) (described in more detail in Appendix C) has been used since 1984 to develop POM inputs (Rexroad, Lucas, and Collins, 1989: 1). This approach combines linear regression and expert judgement to predict out-year requirements based upon, among other things, the aggregated sum (aircraft mission/design level) of past CSIS reports.

The expert judgement comes into play when the Repairable Stock Division Program Manager "scrubs" the output of the ALERT's linear regression-based models. This scrubbing process is similar to that described earlier but it also includes adding requirements for new items not included in the D041 inventory. In those situations where long range forecasts must be made for new items with no historical usage database, ALC specialists must resort to using factor-based computations similar to those prescribed in AFLCR 57-27 (the initial provisioning bible) (Rosenthal, 1991).

Relationship of Recoverable Spares to Life Cycle Phase

In discussing the differences between the initial spares budgeting and provisioning methodologies, it was briefly mentioned that they (the differences) resulted from a lack of available data during the earlier budgeting phase. This section will provide a more in depth analysis of the relationship of recoverable spares cost estimating to an aircraft's life cycle phase. The section begins with definitions of the major life cycle phases and milestones. Following this are subsections which relate these phases to their effect on maintenance plan development, cost estimating methodologies, and the different reasons for cost estimating.

Definitions for Life Cycle Phases/Milestones. Figure 12 illustrates the different weapon system life cycle phases. Before passing from one phase to the next, new acquisition programs must be approved at major milestone reviews (shown between the life cycle phases in Figure 12). Unless specified otherwise, references in this subsection will come from Captain Reynold's 1989 ISSL study.

The DoD components (e.g., Air Force, Army, etc.) continuously monitor their capabilities in relation to new mission requirements. Deficiencies may arise for numerous reasons such as "obsolescence of existing systems, the development of new technologies, [and] the emergence of new threats" (51 & 53). Within the Air Force, the various major commands identify changes in their operational requirements

Nominal Time (In Years):	(0-2)	(2-3)	(3-6)	(3-5)	(15-40)	
System Acquisition Phase:	Concept Exploration Phase	Demonstration/ Validation Phase	Full-Scale Development Phase	Production Phase	Operation And Support Phase	Disposal Phase
	AFSARC & DAB Review @	AFSARC & DAB Review @	AFSARC & DAB Review @	AFSARC & DAB Review @	AFSARC & DAB Review @	
Milestone (MS):	MS 0 Program Initiation	MS I Concept Selection	MS II Program Go Ahead	MS III Production Ratification	MS IV Logistics Readiness/ Support Review	MS V Upgrade/ Replacement Review

Figure 17. Acquisition Life Cycle Phases (TASC, 1989:Ch 5, 11; Reynolds, 1989:52)

by coordinating (with other effected major commands) and then publishing a Statement of Operational Need (SON) (53). The Milestone 0 review authorizes the exploration of alternative solutions to the SON.

Before discussing the subsequent phases and milestone reviews a brief description of the milestone review process may be helpful. The Air Force Systems Acquisition Review Council (AFSARC) reviews the programs at each milestone and makes its recommendations to the Secretary of the Air Force (SAF). The DoD assistant secretaries and directors then meet at the Defense Acquisition Board (DAB) to obtain Secretary of Defense approval for continuing the program into the next life cycle phase (TASC, 1989:Ch 14, 7).

During the concept exploration phase, program management solicits industry to identify solutions to their mission need. A Request For Proposal (RFP) is issued that "includes complete information concerning the mission need, the operational and threat environments, schedule and cost goals, and capability objectives" (55). Each contractor proposal is evaluated, and cost estimates are developed for each alternative. Although the program is still in its infancy, the decisions made as the result of these evaluations will typically lock in about 70 percent of the program's life cycle cost (60). For example, one alternative may include developing a brand new weapon system while another may recommend modifying or buying more of an

existing system. Depending on which route (if any) is taken, there can be a dramatic impact on life cycle costs.

Milestone I approval allows one or more proposed programs (if funding is available) to proceed into the demonstration and validation phase. During this phase paper studies and/or prototype development are used to definitize the system's design and technology (55). Though not as dramatic as in the concept exploration phase, the tradeoff analyses conducted in this phase still have a great impact on life cycle cost. At the end of this stage, approximately 85 percent of the cost has typically been fixed (60).

Milestone II approval allows the system to enter into full-scale development phase. "During this phase, the system, including all essential support equipment and documentation, is designed, developed, fabricated, and tested" (56). Some programs are also granted permission to begin low rate initial production (56). By this time the opportunities to impact life cycle cost have been substantially reduced and at the end of this phase, 95 percent of the costs have already been locked in (60).

Milestone III approval "commits the Air Force to buy the system for operational deployment and moves the system from the developmental environment into full production" (56). It is during this phase that

> mission hardware, support equipment, spares and repair parts, personnel, facilities, etc. necessary to operate and maintain the system are produced, acquired, and assigned. (56-57)

At milestone IV, the Logistics Readiness and Support Review, the system is evaluated to see if it is functioning according to contractual standards. If it isn't, this is the time for the Air Force to exercise any warranties it may have included in the contract. At this point the weapon system enters the longest phase of its life cycle--the operations and support phase. There is typically some overlap of the production and operations phases because production can be scheduled over many years (57).

The final milestone comes at that point in time when the system is "no longer capable of meeting the operational need for which it was acquired" (57). The Major Upgrade or System Replacement Decision (milestone V) decides exactly what its title says it does. Some systems, such as the B-52, are kept in the operational inventory for many years through major modifications; while others enter the final phase of the acquisition life cycle--the disposal phase.

Maintenance Plan Development. One of the major difficulties facing a life cycle cost analyst is that while tradeoff decisions made during the earliest phases typically have the greatest impact on life cycle costs, the availability of data on which to base the decisions is very limited during this period. This is particularly true for Operations & Support cost analysts who must attempt to estimate O&S costs based on immature, ill-defined system designs.

The initial objectives for logistics support are formulated in the concept exploration phase and developed into a Integrated Logistics Support Plan (ISLP). These objectives are refined and individual ISLPs are developed for each alternative approved to enter into the demonstration/validation phase of the contract (TASC, 1989:Ch 5, 8 & 11).

It isn't until completion of the full-scale development phase, however, that the maintenance plan for a new system is fully developed.

> Until that time, the predicted parameters and desired characteristics stated in the Maintenance Concept, will not have been validated. It is virtually impossible to effectively plan for Support and Test Equipment, Spares, Technical Data, Personnel and Training requirements unless the projected maintainability, reliability, and repair level criteria for a given system and its components have been confirmed. (TASC, 1989:Ch 5, 55)

It is obvious from the above quote that recoverable spares are but one of many considerations which occupy the minds of logistics planners. It is also clear that many of the factors impacting spares cost estimating (maintainability, reliability and repair level criteria) are not confirmed until completion of the full-scale development phase. It is important to understand these factors in more detail because they are important cost drivers in recoverable spares cost estimating.

"Maintainability refers to the ease with which a given component/system can be maintained" (TASC, 1989:Ch 5, 18).

This has obvious implications for manpower costs because the "harder" a system is to maintain, the longer it typically takes to do the job. This is also related, however, to the design of recoverable spare parts. Newer aircraft such as the F-16 have been designed with modular components that can be quickly removed when broken and replaced with serviceable spare components to minimize the aircraft maintenance downtime (AFLCP 57-13, 1987:4).

Reliability is another major O&S cost driver. It is defined as

> the probability that the system will satisfy the need for which it was intended in an acceptable manner, for a given period of time, when deployed and used under a given set of operating conditions. (TASC, 1989:Ch 5, 16)

It is easy to see where the reliability factors must be speculative in the early concept exploration phase. System specifications which define "acceptable" performance may not be set in concrete and specific operating conditions (e.g., temperature cycles, flying hour profiles, vibration extremes, etc.) have not been definitized (TASC, 1989:Ch 5, 16).

Reliability is quantified through "terms such as: mean time between failure (MTBF), mean time between maintenance (MTBM), and mean time between repair (MTBR)" (TASC, 1989:Ch 5, 17). The "maintenance factor" discussed in the earlier section on initial spares provisioning factors is based upon another reliability factor known as mean time between demand

(MTBD). While contractor data provides estimates for MTBF, historical data has shown these estimates to be "overly optimistic" (Reynolds, 1989:81). The MTBD is a derivative of the MTBF which has been modified to account for demand drivers not included in the MTBF. For example, the MTBF does not include component failures beyond the contractor's responsibility such as operator error and mishandling. Not every failure leads to a demand and this also is accounted for in the MTBD (Reynolds, 1989:81-82).

The levels of maintenance were also referred to in the earlier discussion on initial spares provisioning. The SMR code identifies what repair actions are permitted at what repair level. As the number of locations with authority to perform a repair action increases, greater numbers of spares are required to maintain adequate working stocks at the different repair facilities. "Level of Repair policies have undergone continuous development and change since the inception of the use of aircraft as a military component" (TASC, 1989:Ch 5, 56). While there were four echelons of repair in World War II, increased maintenance specialization requirements reduced this number to the three level structure--organizational, intermediate and depot--used by most aircraft today. Today, further advances in the need for "highly specialized personnel, test, recalibration, repair equipment, and specialized facilities" are pushing new systems toward a "two level concept" that centralizes most maintenance at the depot level, "leaving only some

test, plug-in replacement (i.e., circuit boards), and pre-flight maintenance at the organizational/field level" (TASC, 1989:Ch 5, 57).

Cost Estimating Methodologies.

The availability of data with which one predicts costs has an important impact upon the cost estimating methodology used. The following major classes of cost estimating methods will be briefly discussed in regards to this factor: 1) parametric, 2) analogy, and 3) engineering (or "bottoms-up").

Parametric Models. Parametric models use mathematical equations known as cost estimating relationships (CERs) to identify the relationship between an item's cost (the dependent variable) and one or more characteristics of that item (the independent variable(s)) (TASC, 1989:Ch 14, 25). These CERs are developed by examining relationships exhibited in past data, and their validity rests upon, among other things, the assumption that the future conditions can be predicted based upon this historical data set.

CERs can be useful in performing trade-off studies during the early stages of an acquisition life cycle. Although final system designs may not be available, different characteristic values may be input into the model to evaluate their effect on cost and design goals may be substituted for firm characteristics. Great care, however,

must be given to ensure that the CER's provide logical conclusions. For example a CER might show that, based on the sample data, engine maintenance costs are directly related to engine size, as measured in thrust. For the new engine being predicted this relationship may fail because

> by increasing the size of the engine, as measured in thrust, the engines can be operated at derated thrust levels and thereby significantly reduce engine maintenance costs. (May, 1982:Ch 3, 5).

The factor based approach to predicting initial spares requirements discussed earlier is an example of a very simple CER. In many cases, such as this one, CERs are relied upon when insufficient data exists to conduct more detailed analysis.

Analogy Method. This methodology depends upon identifying a comparable or "analogous" system to the one being evaluated. Stated simply,

> Analogy estimating begins with the actual cost of a similar existing system, adjust these costs for complexity, technical, or physical differences, and then derives a new system estimate. (TASC, 1989:Ch 14, 27)

The difficulty in this method is in finding a truly "similar" system and then knowing how to adjust costs to account for the differences between the systems. Typically, cost analysts must seek advice from technical experts to evaluate these differences and their impact on cost. Finding "experts" who are familiar with both the analogous

system and the new system can be difficult and the "detailed program and technical definition" of the new system may not be available during the initial phases of the acquisition life cycle (TASC, 1989:Ch 14, 27).

Engineering Estimation. This approach "encompasses a detailed 'build-up' of labor hours, material costs, and overhaul at very finite sub-indentures of the program/activity/item for which cost is to be estimated" (TASC, 1989:Ch 14, 28). As such, it provides the most detailed and accurate cost estimates. Due to its complexity, however, this approach also requires the greatest amount of "calendar time" to perform, and very detailed system data must be available (May, 1982:Ch 3, 8). Since the Maintenance Plan for a new system is typically not definitized until completion of the full-scale development phase, the data required for this approach is not available until that time.

It is frequently the case that a combination of methodologies are used in predicting costs (TASC, 1989:Ch 14, 28-29). For example, an alternative (recommended by two separate studies) to the factor based approach currently used in estimating initial spares requirements is using the Logistics Support Cost (LSC) model (Dement, 1990; Rexroad, Tillia, and Tritle, 1990). The LSC model is an engineering or "bottoms-up" model. Using this approach during early life cycle phases requires that data from analogous systems are modified and input into the model (Dement, 1990:Ch 2).

By combining approaches in this way one can work around some of the limitations unique to the individual methodologies.

Purposes for Cost Estimates. The cost estimating methodologies are not the only thing which may vary depending upon the acquisition life cycle phase, the purpose behind the cost estimate also varies.

The *Program Cost Estimate* (PCE), also known as the Program Office Estimate (POE), is the "program manager's official estimate of the financial resources required to competently conduct the program contained in its Program Management Directive (PMD)" (TASC, 1989:Ch 14, 8). PCEs are maintained throughout the system's life cycle and are used in all the program's

> formal reports--baselines, Selected Acquisition Report (SARs), Program Assessment Reviews (PARS), Command Assessment Reviews (CARs), Secretarial Program Reviews (SPRs), and financial reviews. (TASC, 1989:Ch 14, 8).

An *Independent Cost Analysis* (ICA) is a separate estimate performed by an "honest broker" with no ties to the program office. It is used as a check for the reasonableness of the PCE. "ICAs, by law, (DoD Authorization Act of 1984) must be performed on major defense acquisitions in support of Milestone Decisions" (TASC, 1989:Ch 14, 8). ICAs are briefed to the Air Force Cost Analysis Improvement Group (CAIG) which, in turn, pass their recommendations along for AFSARC milestone decisions. They are also briefed to the OSD CAIG which makes inputs to

DAB milestone reviews. ICAs are also performed on selected programs during the POM process. These estimates are known as Defense Resource Board (DRB) ICAs (TASC, 1989:Ch 14, 8).

Additional estimates include: 1) The *Should Cost Estimate* (SCE) which is developed for individual contracts as a basis for the Government's negotiation objective; 2) A *Most Probable Cost* is used during source selection to check the reasonableness of bidder's cost proposals; and 3) the *Single Best Estimate* results when the IC and PCE processes are combined to arrive at one estimate. Both program office and staff cost analysts combine to form joint estimating team (TASC, 1989:Ch 14, 9).

Data Sources for Recoverable Spares Cost Estimating

Having discussed the different types of cost estimating methodologies and the numerous purposes for which they are developed, it is appropriate to address the data sources available for developing recoverable spares estimates. The following remarks are based upon the research conducted in support of this thesis. The sources will be discussed in the following order: 1) D041, the "Recoverable Consumption Item Requirements System;" 2) H036C, the "Weapon System Cost Retrieval System" (WSCRS); 3) Visibility and Management of Operating and Support Costs (VAMOSC); and 4) Aeronautical Systems Division (ASD) Cost Library.

D041 contains a tremendous amount of recoverable spares data (e.g., usage and inventory data, reliability factors,

item demand rates, condemnations, unit costs, etc.). There were two major obstacles to using this data source for this thesis, however. The primary obstacle was the fact that D041 controls individual spares at the National Stock Number (NSN) level. Since each aircraft contains thousands of individual parts, it was impractical to attempt manual aggregation of this data. The D041 system's Central Secondary Item Stratification (CSIS) reports, used for budget development, do provide spares requirements aggregated to the Mission Design level. "Scrubbed" versions of these reports were obtained from the Repairable Stock Division Program Manager (HQ AFLC/FMBSR).

Other analysts have attempted to use the D041 data and encountered the second major obstacle--D041 was not designed to be a cost analysis tool and the mainframe based program is not "user friendly." Very little computer time is allotted to system inquiries and "what if" exercises. For those brave enough to attempt analysis with D041, data is provided on large magnetic tapes. In one instance, analysts devoted a large amount of effort to learning the D041 software program and interpreting the data they received on the magnetic tapes only to find that there were gaps in the data rendering it useless (Dement, 1991).

The Weapon System Cost Retrieval System (WSCRS) was a better source of data for this thesis. The WSCRS system

> collects and assembles the historical depot maintenance cost expenditures, and the base level and depot level

> condemnation cost expenditures, for the major USAF aircraft and missile weapon systems. . . . WSCRS also collects and assembles historical weapon system program data by weapon system standard MDS. The weapon system's actual and programmed utilization data are collected by fiscal year. (AFLCM 173-264, 1990:7)

Unlike D041, the WSCRS system was originally designed and is maintained by HQ AFLC/FMC to support cost analysis projects (AFLCM 173-264, 1990:5). Request for WSCRS data (which begins with FY 1975) must be addressed to HQ AFLC/FMC and the data is provided in hard copy. Several different aggregate levels of data can be requested, including mission design series (MDS), fleet (MD), and mission (i.e., fighter, bomber, cargo, etc.). Data can be further divided to weapon system work breakdown structure (Steinlegy, 1991).

The VAMOSC system, as its name implies, was originally designed in the mid-1970's to provide increased management insight into weapon system costs (May, 1982:Ch 5, 13). Through the years this system has been modified and updated in order to fulfill its original promise. Several factors have impaired this process and the system is still in need of maturation.

Responsibility for VAMOSC has switched hands on different occasions. The Air Force Cost Center is the present OPR but they are looking for an alternative host site. Manpower and facilities limitations have impaired VAMOSC development at the Cost Center. When researched for this thesis, only three quarters of data were input into the VAMOSC automated system. Past history at the NSN level was

available on microfiche; but given the thesis time constraints, this formidable aggregation task was even less appealing than the D041 system (Masserro, 1991).

The ASD Cost Library was also briefly evaluated. It appeared to be an excellent source for identifying historical cost methodologies used by various programs but it contained very little cost data with which to conduct original research.

Appendix C: Models Which Predict Recoverable Spares Costs

Introduction

The purpose of this appendix is to evaluate selected models which can be used to predict recoverable spares costs. The intent is not to provide in-depth operating instructions but rather to familiarize the reader with the models and their applicability. While not exhaustive, the appendix includes both engineering or "bottoms-up" models and parametric models selected for: 1) their general (as opposed to SPO specific) applicability, and 2) their prominent use in the AFLC community [one parametric model, developed by Rand Corporation, was included even though it is not in "prominent" use. It was evaluated simply because there were few parametric models in the literature review and this model was evaluated by the AFLC "Initial Spares Working Group" as a potential candidate for predicting initial spares requirements]. The text begins with the analyses for the following parametric models: 1) Rand study 2) Modular Life Cycle Cost Model (MLCCM); and 3) Air Logistics Early Requirements Technique (ALERT). Next, the following engineering models are evaluated: 1) D041, the "Weapon System Cost Retrieval System;" 2) AFLC Form 614, the initial spares requirements computation form; 3) Logistics Support Cost (LSC) Model; 4) Mod-Multi-Echelon Technique for Recoverable Item Control (Mod-METRIC); and 5) Dyna-METRIC.

A standard format is used during each analysis to simplify comparisons between the models.

Rand Study

All references in this subsection, unless identified otherwise, come from the developer's (see below) 1980 report, Estimating USAF Aircraft Recoverable Spares Investment.

Developer(s): K.J. Hoffmayer, F.W. Finnegan, Jr., and W.H. Rogers of the Rand Corporation, August 1980.

Model Purpose: The model is an update to a previous 1976 Rand model for estimating USAF aircraft recoverable spares investment. It includes models for estimating total replenishment spares requirements at the major subsystem level (airframe, avionics, and propulsion) and for estimating condemnation spares requirements at the same level (v). An attempt was made to develop an initial spares model but this was unsuccessful due to limited data availability (23). The models provide annual estimates for peacetime operating stock. War readiness material, spare engines, and engine spare parts are excluded. The models are intended for use prior to the preproduction or deployment decision stages of the acquisition life cycle (iii).

Model Algorithm: The study states that a logarithmic form was chosen to develop the CERs due to its (logarithmic CERs in general) superior handling of heteroscedasticity and

its more "real world" multiplicative nature (11, 15). They fail to clearly state whether the transformations are natural (ln) or common (log) logarithmic in nature.

Table 17 shows the cost drivers used on each CER.

Table 17

Subsystem CER Independent Variables (12-14)

Airframe CER	Avionics CER	Propulsion CER
Total active aircraft in MDS inventory	Total active aircraft in MDS inventory	Total number of installed engines in the MDS force
Airframe flyaway cost	Avionics flyaway cost	Propulsion flyaway cost
Peak flying hours per MDS per year	Dummy variable for bomber	
	Dummy variable for reconnaissance	
	Dummy variable for fighter/attack	
	Dummy variable for cargo	
	Dummy variable for tanker	

The following logarithmic form is common to each of the subsystem CERs (11):

$$\log Y_{it} = \log \alpha + \sum_j \beta_j \log X_{ijt} + \epsilon_{it} \qquad (12)$$

Where

Y_{it} = investment in POS spares inventory of aircraft subsystem i at time t.

X_{ijt} = the jth characteristic observed on aircraft subsystem i at time t.

α and β_j = regression coefficients

e_{it} = the error for aircraft subsystem i at time t. The errors are assumed to be independent across subsystems but correlated over time with subsystem.

<u>Data Inputs and Sources</u>: Cost data from 1975 to 1978 was provided for the following aircraft (7):

A-7D	C-5A	RF-4C	F-111D
B-52D	KC-135A	F-4D	F-111F
B-52G	C-141A	F-4E	T-37B
B-52H	F-4C	F-111A	T-38A

Specific data elements and sources are as follows (4-5):

D041 "Recoverable Consumption Item Requirements System:"

National Stock Number (NSN)
Unit Price (in then-year dollars)
Program Begin Date (earliest record of use)
Program Selection Code (Material Program managing part)
Organization Field Maintenance (OFM) Total Demand Rate (total item demand expressed in terms appropriate for its material program)
Base Level Condemnations (NSN level condemnations at base level)
Depot Level Condemnations (NSN level condemnations at depot level)
Total Overhaul Condemnations (NSN level condemnations resulting from planned overhauls)
Total Peacetime Operating Stock Assets
Application (the mission design series (MDS) or other stock number using the item)
Quantity Per Application

J041 "Procurement History File:"

National Stock Number (NSN)
Contract Date
Amount of Contract ($)
Quantity Procured

"Aerospace Vehicle Inventory Status and Utilization and Reporting System" (AVISURS):

Aircraft MDS
Calendar Year and Month
Flying Hours
Sorties
Landings
Average Number of Possessed Aircraft

Other data used in the model development was obtained from the following sources:

* TO 0025-30, Technical Manual, "Unit Cost of Aircraft, Guided Missiles, and Engines."
* USAF Statistical Digests
* PA, "USAF Program, Aerospace Vehicles and Flying Hours."

<u>Assessment</u>: The accuracy of the models provided are difficult to assess due to the minimal coverage of model diagnostics. The R^2 provided for the propulsion model has poor statistics: R^2 of .5841 and SEE of .67318. Because Rand does not specify which base was used (natural or common) the reader is left to guess at the significance of the standard error of the estimate (the SEE is a measure of prediction accuracy for a transformation using the natural base)(Murphy, 1990-1991).

It is unclear if the logarithmic form is really appropriate because they never actually state that they observed heteroscedasticity in the data; or why they feel a multiplicative equation is more "real world". They fail to document any diagnostics performed or other models attempted and discarded.

The manner in which subsystem flyaway costs were included in each of the subsystem CERs may be questioned. One tenet of the integrated logistics support philosophy is that as an item's reliability improves, the reduction in its operations and support costs over its life cycle more than compensates for its increased acquisition cost (which has resulted from its improved reliability) (TASC, 1989:Ch 5,

25). The multiplicative nature of the subsystem CERs does not account for this belief logically. According to these CERs, increased CERs will always result in greater spares costs.

Although the source text does not explain its rationale for using component flyaway costs, a case can be made that life cycle O&S costs reduce with improved reliability for reasons other than reduced spares requirements. After all, replenishment spares costs are only a subset of the total O&S costs. More reliable parts should fail less often and therefore cost less for maintenance and repair. If RAND believes that these types of savings exceed the increased spares costs associated with more expensive components, then their logic is not contradictory to reliability theory.

This methodology was evaluated by the Initial Spares Working Group comprised of twenty two members representing HQ AFLC, ASD and HQ AFSC. They concluded that the model's database should be updated and a clear distinction made between initial and replenishment spares before they could use the model (Rexroad, Tillia, and Tritle, 1990:11).

<u>Modular Life Cycle Cost Model (MLCCM)</u>

All references in this subsection, unless specified otherwise, come from Grumman Aerospace Corporation's 1986 report entitled <u>Modular Life Cycle Cost Model for Advanced Aircraft Systems, Cost Methodology Development and</u>

Application. The authors were R. Isaacs, N. Montanaro, and F. Olivo.

Developer(s): Grumman Corporation, Program Team directed by Mr. R. Isaacs, September 1986.

Model Purpose: The MLCCM is a parametric-based series of models for

> predicting advanced technology aircraft costs, to the major subsystem levels, for the Research, Development, Test, and Evaluation, Production, Initial Support, and Operations and Support phases of the system life cycle during conceptual and preliminary design. (iii)

Initial and replenishment spares are but subsets of the overall costs within the production and O&S periods, respectively. Their cost is broken out for 14 subsystems (structure, crew system, landing gear, flight control, cargo handling, engines, engine installation, environmental control systems, electrical, hydraulic/pneumatic, fuel system, avionics, armament, auxiliary power unit) (11) for two classes of aircraft (fighter/attack/bomber and cargo/transport/ tanker)(x).

Model Algorithm: Because the MLCCM was developed as a tool for conducting trade studies during the design stage, the CERs were developed using a Work Breakdown Structure (WBS) format. In this way the design engineers would be able to relate costs to the WBS elements for which they were responsible. Step-wise regression was used to develop log-linear regression equations. Again, it is unclear if they used natural or common base transformations. They limited,

for most cases, the number of parameters in any CER to one third the number of data points (47-48). While it makes sense to preserve degrees of freedom by limiting the number of variables used (compared to the number of data points), it isn't clear why the developers chose one third as the criteria ratio. The developers provide no explanation for this criteria.

Data Inputs and Sources: Cost data was derived from several sources including: "Visibility and Management of Operating Support Costs" (VAMOSC) system, AFR 173-13 Factors, and the 1975/1976 Operating and Support Cost Estimating Report. Independent variable technical data sources include: Standard Aircraft Characteristics (SAC) charts, group weight statements, technical orders, and the manufacturer.

> The SAC charts were used to obtain data on engine design and performance, fuel and tankage, armament, loading and aircraft performance, development dates, etc. Weights, areas, volumes, dimensions, and general aircraft design characteristics were obtained from the group weight statements and the manufacturers. Flight manuals were used for data on electrical, fluid power, and flight actuator systems and for general aircraft design characteristics as well [note that not all of these variables are used in the replenishment spares CERs]. (13)

Assessment: The fact that the models were developed with obligation data brings with it all the uncertainty previously discussed in the data problem section. The report admits the need for better cost data inputs (219).

The model statistics provided were not complete. R values were provided as opposed to the R^2 statistic commonly seen. The R^2 values for 5 of the 14 subsystems in the fighter/attack/bomber class of aircraft were poor (less than .7) (165-169). No discussion of model diagnostics was provided.

Air Logistics Early Requirements Technique (ALERT)

Unless stated otherwise, references in this subsection will come from a 1989 report entitled Air Logistics Early Requirements Technique (ALERT) FY90-94 Program Objective Memorandum (POM) Forecast. The authors were Adrienne Rexroad, Robert Lucas, and Larry Collins.

Developer(s): AFLC/MMM, 1984.

Model Purpose: ALERT has been used since 1984 by HQ AFLC as the starting point for developing BP15 aircraft peacetime spares Program Objective Memorandum (POM) inputs. It is the "starting point" because the output from ALERT is scrubbed by the BP15 Program Manager prior to its submittal (1).

Model Algorithm: The CERs developed used straight linear regression to predict the first year of requirements. This first year's estimate is then used as historical input for the next four years' predictions--a regression technique which referred to as "bootstrapping." (2).

Data Inputs and Sources: The dependent variable data used were the requirements submitted in the last Budget

Estimate Submission (BES). There were a total of four independent variables used (not all at once) in the CERs: 1) Mission Design Series buy requirements from the D041 "Recoverable Consumption Item Requirements System," 2) Average Fleet Value, as calculated by USAF/AC, 3) the reciprocal of the estimated Present Fleet Age, also provided by USAF/AC, and 4) Chronological Year.

Assessment: Only six of the sixteen weapon system class CERs had adjusted R^2 values exceeding .7 and only one class exceeded .75. The BP Manager scrub that followed subsequent to the ALERT run changed the input values further. The BP Manager is critical of the D041 input data since it uses the June data run (a quarter not updated by three of the five ALCs). He also questioned the logic of using the fleet value as a cost driver. USAF/AC based their estimate of fleet value on projected future flying hour programs which decrease over time. The fleet values, therefore, decrease over time. The spares requirement, however, logically gets larger as the fleet gets older (7).

D041

Unless stated otherwise, references in this subsection will come from a June 1987 AFLC training program entitled "Introduction to D041 Requirements System" (course # LMMIM06).

Developer(s): Unidentified. Managed by HQ AFLC/MM (Material Management Division).

Model Purpose: The Recoverable Consumption Item Requirements Computation System (D041) actually serves several functions. In addition to determining buy requirements, D041 computations: 1) assist in managing depot repair requirements, 2) develop Central Secondary Item Stratification (CSIS) lists for spares budget development, 3) determine spares contract termination requirements, 4) report excess requirements for disposal action, and 5) provide for control of distribution of the spares requirements (Ch 1, 5-6).

D041 can hardly be classified as simply a cost model. Because it is the system used to execute the replenishment spares budget, however, other cost models, such as the Logistics Support Model, are compared to D041 to validate their results (Alexander, Brookey, Erhart, Fulton, Hofmann, and Shutak, 1990:I-2; Dement, 1990). For this reason it is included in the appendix

Model Algorithm: Figure 13 provides a summary level view of the basic requirements computation process employed by D041. The methodology is similar to that used for initial spares provisioning (AFLCR 57-27) in that factors are developed to predict future requirements. It differs, however, in that the initial spares provisioning factor estimates are typically manually developed by the ALC equipment specialists based upon contractor inputs and their own expertise, while the automated D041 factors can be updated based on historical usage recorded during the

* USAGE / PAST PROGRAM = FACTOR

* FACTOR x FUTURE PROGRAM = PROJECTED USAGE

* PROJECTED USAGE

  + STOCK LEVELS

  + WAR READINESS MATERIALS

  + ADDITIVE REQUIREMENTS

  = GROSS REQUIREMENT

* GROSS REQUIREMENT

  - ASSETS (Serviceable assets plus base and depot repairables)

  = NET REQUIREMENT

Figure 13. D041 Requirements Determination Methodology (Ch 1, 2 & Ch 7, 1)

initial spares coverage period (an average of two years worth of data). Figure 14 provides examples of the D041 requirements computation factors. These factors, developed on past usage, are then applied to the projected future flying programs to predict future spares requirements. Stock level requirements, war readiness material requirements, and additives are added to these predicted levels to arrive at gross requirements. Serviceable assets on hand and those projected to be repaired at base and depot

* Base Reparable Generations = Base RTS + Base NRTS + Base Condemnations
* Depot Reparable Generations = Job Routed Condemnations + NJR Generations
* Depot O/H Condemnation % = Depot O/H Condemnations / (Depot O/H Condemnations + Depot O/H Repaired)
* Item Past Program = Application Past Program x QPA x Application %
* Usage Element / Past Program = Factor

Where

RTS = Repairable This Station

NRTS = Not Repairable This Station

NJR = Non-Job Routed

O/H = Overhaul

QPA = Quantity Per Application

Figure 14. Example D041 Requirements Factors (Ch 7, 1)

facilities are then subtracted to arrive at the net buy requirement (Ch 1, 1).

Data Inputs and Sources: The D041 system is actually at the center of numerous other computerized systems that feed data into it. Chapter 10 of AFLCR 57-4 describes these input systems in detail. There are three major categories of input data: 1) programmatic information, 2) historical spares usage data, and 3) inventory assets information. The "Worldwide Stock Balance and Consumption Report" (SB&CR) provided by the D104 system provides two of these categories--usage and assets. Because it is the major data contributor, the data cutoff dates for the quarterly D041 runs are aligned with the SB&CR cutoff dates--30 June, 30 September, 31 December, and 31 March (Ch 2, 2).

Assessment: It is difficult to evaluate D041 without examining the many contributing systems which feed into it. For example, the Modified Dyna-METRIC model provides factors used by D041 for determining War Readiness Spares Kits (WRSKs) (Oster, Sakulich, and Stone, 1989:3). Additionally, D041 uses inputs from the Aircraft Availability Model (AAM) to determine its base safety level stock (Alexander, Brookey, Erhart, Fulton, Hofmann, and Shutak, 1989:IX-16). As a result, D041 shares in the same benefits and drawbacks associated with its input systems. In the preceding examples, both models allow D041 to optimize the repair capability gained for these spares categories within a given budget constraint. Marginal analysis techniques are

utilized to examine the relationship between final assemblies (e.g., a "black box"), known as the line replaceable units (LRUs), and their various, less expensive components (e.g., a circuit board), known as shop replaceable units (SRUs) (Alexander, Brookey, Erhart, Fulton, Hofmann, and Shutak, 1989:IX-16; Oster, Sakulich, and Stone, 1989:2). If the components within an assembly that are most likely to fail can be identified, it is more economical to stock a number of the SRUs rather than purchasing numerous, more expensive LRUs to arrive at the same amount of repair capability.

As previously stated, the D041 system is the standard by which other models are evaluated for their validity. That is not to say that it is a perfect system by any means. The D041 product used for budget development, known as the Central Secondary Item Stratification (CSIS) report, must be thoroughly scrubbed by the Repairable Stock Division Program Manager and the ALC inventory management and equipment specialists. According to the Repairable Stock Division Program Manager, it is not uncommon for the CSIS reports to contain numerous errors (e.g., data entry problems) that, before being "scrubbed," predict requirements which are substantially off the mark (Rosenthal, 1991).

The D041 system was also not designed as a cost estimating tool. It manages recoverable spares down to the Federal Stock Number level and it can aggregate requirements to the aircraft mission design level. It has no built in

capability to aggregate its data to other levels (such as work unit code, for example). For this reason it is impractical to think of the D041 as a cost estimating tool. It is too inflexible to perform what-if type exercises and very little computer time is made available for system inquiries (Artley, 1991).

AFLC Form 614

Unless stated otherwise, references in this subsection will come from a 1989 report entitled Analysis of Initial Spares Support Lists (ISSL). This report was written by a team headed by Captain Steve Reynolds.

Developer(s): Unidentified. Policy for initial requirements determination is made by HQ AFLC/MMMIE. The AFLC Form 614s have, historically, been manually prepared. This process is being automated by XRII on a system known as the Initial Requirements Determination (IRD) system. The IRD is currently in system validation test and should be on line by the end of summer 1991 (Horner, 1991).

Model Purpose: The AFLC Form 614 computations are the "initial spares" equivalent of the those performed by D041 to determine replenishment spares buy requirements. Unlike D041, however, the AFLC Form 614 process has not been used in the budget development process. Initial spares budgets are developed using a factor based approach that relates spares requirements to aircraft flyaway costs (Rexroad, Tillia, and Tritle, 1990:1). This approach has been used

because the numerous data inputs required in the AFLC Form 614 process are typically not available until completion of the full-scale development life cycle phase (TASC, 1989:Ch 5, 55). Budget wedges must be estimated prior to this time and so HQ AFLC/FMBSR, the agency responsible for the initial spares budget, has fallen back on the factor based approach.

The factor based method has been criticized for its lack of lack of insight into underlying causal relationships and alternative cost models are being evaluated as candidates to replace it. The Logistics Support Cost (LSC) Model (the next model evaluated in this appendix) has been recommended by two studies for this purpose (Dement, 1990; Rexroad, Tillia, and Tritle, 1990). The LSC model, however, presents the same data input scarcity problem which has prevented the AFLC Form 614 process from doing the job all along. Although the AFLC Form 614 process has not been used as a cost estimating tool in the past, it is included in this appendix because it seems that the same work around being suggested for the LSC data problem (i.e., using data from analogous systems (Dement, 1990:Ch 2)) would work for it also.

Model Algorithm: The AFLC Form 614 computations are similar in nature to the D041 computations. As stated in the D041 analysis, the provisioning factors used in the AFLC Form 614 computations are estimates based upon contractor inputs and the expertise of the equipment specialist(s) making the estimate. This contrasts with the D041 factors

which may be adjusted based upon observations of the items' performance during the initial spare coverage period (an average of two years) (16). Figure 15 provides examples of the AFLC Form 614 requirements computations.

Data Inputs and Sources: The following provisioning factors are provided by the equipment specialist(-) during the provisioning process:

Maintenance Factor
Overhaul Replacement Percent
Base Condemnation Percent
Depot Condemnation Percent
Not Reparable This Station (NRTS) Percent

In addition to these factors, information concerning the weapon system's operational program is collected by the System Program Manager on checklists such the AFLCR 57-27 (18). Together, these data provide the inputs required to compute the AFLC Form 614 initial spares requirements.

Assessment: Besides the previously mentioned data availability problems, there are two important deficiencies inherent in the AFLC Form 614 process that were identified in Capt Reynold's ISSL study.

The first problem is that the 614 worksheets do not maximize the repair capability for a given budget constraint. The reason this is so is that no consideration is given to the LRU/SRU indenture relationships (41). It is probable, therefore, that a better mix of LRUs and SRUs could provide the same amount of repair capability at a

DLM NJR Annual Demand = Average Month Program x 12 x QPEI (for engine O/H or programmed depot maintenance) or QPNHRA (for MISTR items) x Applications % x NJR Program % x NJR Replacement %

DLM JR Annual Demand = Average Month Program x 12 x QPEI or QPNHRA x (1 - NJR Program %) x JR Condemnation % x Application %

Total DLM Annual Demand = DLM NJR Annual Demand + DLM JR Annual Demand

OIM Annual Demand = Average Month Program x 12 x QPEI x OIM Demand Rate x Applications %

Where

DLM = Depot Level Maintenance

NJR = Non-Job Routed

QPEI = Quantity Per End Item

JR = Job Routed

O/H = Overhaul

MISTR = Management of Items Subject to Repair

QPNHRA = Quantity Per Next Higher Recoverable Assembly

OIM = Organizational or Intermediate Maintenance

Figure 15. Example AFLC Form 614 Requirements Computations (AFLCR 57-27, 1986: 5-6)

cheaper price; or, using the same budget, a greater repair capability could be obtained.

The second problem is that the 614 worksheets have "no direct linkage to readiness and availability objective" as required by DoD mandate (DODI 4140.42)(41). The 614 worksheet computations attempt to fill backorders for items during the initial spares coverage period, but there is no direct link made between filling backorders and meeting a readiness objective. Not all parts are critical for an aircraft to be "ready" or "available" to perform its mission.

Logistics Support Cost (LSC) Model

Unless stated otherwise, references in this subsection will come from an independent validation of the LSC Model (version 2.0) performed by Management Consulting & Research, Inc. (MCR). The final report, written by Areve B. Alexander, Lori E. Brookey, Robert J. Erhart, Sarah J. Fulton, Dr. Jerry D. Hofmann and Michael D. Shutak, is dated 15 May 1990.

Developer(s): Original version (1.0) was developed in 1975 by the Air Force Air Logistics Division (AFALD) to run on a mainframe computer (II-1). The current personal computer based version (2.2) was released in 1991 and developed by HQ AFLC/FMC (then ACC) (Passage, 1991).

Model Purpose: The current LSC model can be used to provide estimates for the following life cycle costs: 1)

initial spares (including base and depot safety stock), 2) replenishment spares, 3) depot maintenance, 4) second destination transportation, and 5) Repair Support Division (RSD) Stock Fund (Passage, 1991).

The LSC model is accepted as a valid estimating model by both the AF and OSD Cost Analysis Improvement Groups (CAIG). Among its recent applications, the LSC model was used to perform independent cost analyses for the Advanced Tactical Fighter (ATF), C-17, Global Positioning System, and Joint Stars program offices (Passage, 1991).

Model Algorithm: The LSC model performs computations similar to those used by D041 and the AFLC Form 614 process. It provides cost estimates for individual reparable items (LRU or SRU) and then aggregates these costs to the subsystem and system level (III-2).

Numerous assumptions are incorporated into the LSC model. A selection of these assumptions include:

1) "The logistics support processes and costs of an item are mathematically independent of those of other items, even items physically related to it" (III-2).

2) "The support cost calculation of one item does not affect the support costs calculation for any other item" (III-2).

3) "The model assumes the standard USAF maintenance concepts for the repair of reparable components from aircraft apply" (III-3). For this reason, the model can handle three level or two level maintenance scenarios.

4) A Poisson probability function is used in the modeling of queues (III-8).

5) Little's equation is used to calculate the number of items repaired monthly at the intermediate level (III-7).

6) The intermediate level repair process meets the following requirements:

a. The number of arrivals per unit of time is described by a Poisson distribution.

b. Customers are served in order of arrival.

c. There is one server or serving facility.

d. The mean arrival rate is less than the mean service rate.

e. The waiting space for customers is infinite; that is, no customers are turned away or leave of their own accord, due to limited waiting space or slow service times.

f. The population of customers is finite.

g. Service times are describe by a deterministic distribution function. (III-9)

Figure 16 provides examples of the computations used by the LSC model.

Data Inputs and Sources: The LSC model contains five data input files: 1) system; 2) hardware; 3) cost; 4) support equipment; and 5) SRU factor file. Tables 18 through 20 identify required data inputs and data sources for three of these files to illustrate the large amount of data required in the LSC model [the system file, not shown below, contains another 29 data inputs]. It is the large number of data inputs which prohibits this type of model from being used in the early acquisition phase without resorting to analogous systems data or design goals to complete the data files.

Total Generations (TOTGENS) per year = (TOTFLHR * QPA * UF) / (RP / ADJ)

Peak Generations (PKGENS) per month = (PKFFHR * QPA * UF) / (RP /ADJ)

Base Pipeline Spares (DMDMEAN) = PKGENS * ((NRTS + BCOND) * OST) + (RTS * BRCT)

Depot Pipeline Spares (DPIPE) = PKGENS * NRTS * DRCT * (1 - DCOND)

Condemnation Spares (TOTCND) = TOTGENS * (BCOND + (NRTS * DCOND))

Replenishment Spares = TOTCND $ * Demand Volitility Factor {2.15}

Where

TOTFLHR = Total fleet flying hours
QPA = Quantity per application (on aircraft)
UF = Utilization factor (operating hrs/flying hrs)
RP = Reliability factor; MTBR for spares
ADJ = Derating factor to simulate reliability growth
PKFFHR = Peak fleet flying hours per month (for depot pipeline spares this is the sum of base peak hrs)
NRTS = Not Repairable This Station percent
Bcond = Base Condemnation Rate
RTS = Repairable This Station percent
OST = Weighted avg order & ship time (in days)
BRCT = Base repair cycle time (in days)
DRCT = Depot repair cycle time (in days)
DCOND = Depot Condmnation Rate

Figure 16. Example LSC Model Requirements Computations (Passage, 1991)

Table 18

LSC Hardware File Inputs & Sources

DATA INPUT	SOURCE
# of subsystems	SPO/SPM
WUC identification	SPO/SPM/ALD
System name	SPO/SPM/ALD
# of LRU/SRU records	SPO/SPM/ALD
Design or target mean time to repair at the organizational level	SPO/SPM/ALD
Design of target mean time between removals	SPO/SPM/ALD
Engineering change order indicator	LSC USER
WUC identification of LRU/SRU	SPO/SPM/ALD
Description or name of LRU/SRU	SPO/SPM/ALD
Stocklisted item indicator	SPO/SPM/ALD
Quantity per application	SPO/SPM/ALD
Expendability, recoverability, reparability category (ERRC) record to be read from System File	LSC USER
LRU/SRU mean time between removal	SPO/SPM/ALD
LRU/SRU mean time between demand	SPO/SPM/ALD
Average # of hours for depot to repair an SRU from this LRU	ALC/SPO/SPM/ALD

Table 18 (Continued)

LSC Hardware File Inputs & Sources (Passage, 1990)

DATA INPUT	SOURCE
Not reparable this station %	SPO/SPM/ALD
Base condemnation rate	SPO/SPM/ALD
Depot condemnation rate	ALC/SPO/SPM/ALD
Average # of labor hours to repair this item at the depot	ALC/SPO/SPM/ALD
Labor rate for Interim Contractor Support (ICS) or RIW repair	SPO/SPM/AFLCP 173-10
Fraction of time this LRU is repaired at base by removal of an SRU and sending an SRU to depot	ALC/SPO/SPM
LRU/SRU weight (in lbs)	SPO/SPM/ALD
SRU indicator: 1 = LRU with unknown SRUs; 2 = LRU with SRU data to follow; 3 = item is an SRU	SPO/SPM/ALD
Utilization Factor - ratio of operating hours to flying hours	SPO/SPM/ALD
User defined category indicator	LSC USER
Derating index indicator	LSC USER

Table 19

LSC Support Equipment File Inputs & Sources (Passage, 1990)

DATA INPUT	SOURCE
Index value identifying type of support equipment (SE)	SPO/SPM/ALD
# of years of SE costs	LSC USER
Cost of SE inherited from another Program	SPO/SPM
Cost of SE developed for this Program	SPO/COST TEAM

Table 20

LSC Cost File Inputs & Sources (Passage, 1990)

DATA INPUT	SOURCE
5 digit Work Unit Code (WUC) matching Hardware File WUC for same item	SPO/SPM/ALD
# of cost fields on this line	LSC USER
Lot average unit cost for each year specified by second input above	SPO COST TEAM

Assessment: As previously stated, the LSC model has been approved for use by both the AF and OSD CAIGs and it was independently validated by MCR. The LSC was one of the two models chosen (out of a group of six alternatives) by an Initial Spares Working Group as an alternative to the current factor based approach to developing initial spares budgets (Rexroad, Tillia, and Tritle, 1990). Another study performed by Capt Anne Dement, an ALD operations research analyst, attempted to validate the use of a demand based

budget estimating model (i.e., the LSC model) during the early acquisition phases by using it to estimate initial spares costs for the Advanced Tactical Fighter. According to the report's Executive Summary, "the test showed the approach was executable, provided a reasonable estimate, and offered several significant advantages over current estimating techniques" (Dement, 1990).

Even with all of these factors in its favor, the LSC model is still not without its shortcomings. Like the AFLC Form 614 process, the LSC model has no marginal analysis capability to optimize the LRU/SRU mix for a given budget constraint. The model also doesn't include spares required for programmed depot maintenance and component overhaul in its calculations (Dement, 1990:Append 1, Sec 2.2.2). Finally, the out of production and demand volatility factors used in the model need additional analysis to validate them. In both cases these factors make significant contribution to the overall spares requirements and yet little research has been conducted to validate their default values [see Chapter two of this thesis for a description of the demand volatility factor history].

Mod-METRIC

Developer(s): John A. Muckstadt developed Mod-METRIC based upon the earlier Multi-Echelon Technique for Recoverable Item Control (METRIC) developed by Craig C. Sherbrooke of the RAND Corporation (Muckstaadt, 1973:472).

Model Purpose: While METRIC was designed for determining both the requirements and distribution of recoverable spares in a two-echelon (base and depot) inventory system (Muckstadt, 1973:472), Mod-METRIC also "permits two levels of parts to be considered, an assembly and its components" (Muckstadt, 1973:474). In other words, Mod-METRIC uses marginal analysis techniques to identify the optimum mix of LRUs and SRUs for a given budget constraint.

Current Mod-METRIC applications include "initial provisioning, engine requirement computations and redistribution of spares" (AFLCP 57-13, 1987:3).

Model Algorithm: Keeping weapon systems in serviceable condition is the goal of the Air Force maintenance process described in this paragraph (AFLCP 57-13, 1987:3-4). Modern weapon systems have modular designs to allow failed LRUs or SRUs to simply be removed and replaced from the base stock of serviceable spares. The stock is replenished when the base repairs the failed item and places it in the stock. If the base cannot repair the item, it is sent to the depot for repair and the base requests that its serviceable spares stock be resupplied from the depot stock. It is clear that the stock levels of serviceable items impact the performance of this system. If demanded items cannot be supplied from the base stock, the aircraft goes into not mission capable (NMC) status until the item is: 1) repaired at the base level, 2) repaired at the depot level, or 3) obtained from the depot stock (if available). When items demanded at the

base level cannot be supplied from base stock, the items are considered on backorder. One backorder day equates to one item on backorder for one day (AFLCP 57-13, 1987:8).

Both METRIC and MOD-METRIC model this maintenance process. The objective function for METRIC is to determine the amount of LRU stock and where to place it (base or depot) that will minimize the number of backorder days for a given budget constraint (AFLCP 57-13,1987:10). The objective function for MOD-METRIC focuses on a single LRU and determines the optimum mix of the LRU and its associated SRUs that will minimize the number of backorder days for the LRU for a given budget constraint [Another METRIC based model known as COMBINE supplements the MOD-METRIC model to solve problems with many LRU-SRU groups considered simultaneously] (AFLCP 57-13, 1987:10).

Both METRIC and Mod-METRIC have the same assumptions (AFLCP 57-13,1987:8):

a. No lateral resupply between bases.
b. No batching of items before repair is started on an item (infinite channel queuing assumption).
c. The level at which repair is performed depends only on the complexity of the repair, not on existing workload.
d. Repair times are statistically independent.
e. A stationary compound Poisson probability distribution describes the demand process for each item.
f. Simultaneous failures of SRUs do not occur.
g. A failure of one type of item is statistically independent of those that occur for any other type of item.

Both the METRIC and MOD-METRIC models employ operations science techniques such as Lagrangian multipliers and

Fibonnacci searches. The scope of this paper limits the following algorithm discussion (AFLCP 57-13, 1987:9-10) to a more general level. As previously stated, METRIC determines optimum LRU stock levels for a given budget constraint. Because partial LRUs are not considered, the cost of the stock level will probably not equal the budget constraint exactly. The Lagrangian multipliers are part of a marginal analysis process that evaluates the reduction in backorders per additional dollar invested in the various LRUs which compose the weapon system and provides a solution very close to the budget constraint. The model then increments the budget and determines the optimum stock level for the new budget constraint. This allows one to plot backorder performance versus cost.

The MOD-METRIC model has the added complexity of evaluating the optimum mix of an LRU and its SRUs. The available budget is first allocated between purchasing whole LRUs and the associated SRUs using the Fibonnacci search. After a portion of the budget has been allocated to SRUs, the same marginal analysis employed by METRIC is used to determine the optimum number of the various SRUs which compose the LRU and to distribute these SRUs between the bases and the depot. The budget is then incremented and the process is repeated for the new budget constraint. Again, performance versus cost can be plotted.

Data Inputs: Data files for running mod-METRIC can be created at HQ AFLC using CREATE (a Honeywell 6000 series

computer). Mod-METRIC may be run from other systems given that specific formats (addressed in chapter eight of AFLCP 57-13) are adhered to in developing the data files. The following data inputs are required (AFLCP 57-13, 1987:15):

Flying hour program data:

1) Number of bases.
2) Flying hours per month per base.
3) Order and shipping time per base.

Recoverable item data:

1) Identification.
2) Unit cost.
3) Mean time between demand.
4) Not repairable this station percentage.
5) Condemnation percentage.
6) Quantity per next higher application.
7) Base repair time.
8) Depot repair time.
9) Procurement lead time.
10). Item-dependent order and ship time.

Computer program control data: This data category refers to information provided by the user when prompted by a series of questions from an interactive preprocessor called BUILD. The answers to these questions (e.g., user-id, target budget value, size of increment between successive budgets evaluated, etc.) are required for the program to know the specifics of what type of output the user is seeking (AFLCP 57-13, 1987:15-17).

<u>Assessment</u>: The F-15 program was one of the first weapon systems to employ the MOD-METRIC model. Previous weapon systems made use of the methodology prescribed in AFLCR 57-27 (still an accepted approach). This methodology "was written and published when maximum-base-self-

sufficiency was an accepted maintenance concept" (Huff, 1979:9). This concept does not allow for optimization of resources because individual bases, using this approach, tend to purchase more LRUs and less SRUs to prevent LRU backorders. More repair parts are required at each base in order for them to be self-sufficient. The MOD-METRIC model is credited as one of the factors behind the F-15 program's ability to complete initial spares provisioning within budget (Huff, 1979:10-11).

The Mod-METRIC model is not without limitations, however. Because the Mod-METRIC model assumes that demand is described by a stationary compound Poisson probability distribution and that each item is equally critical, critics argue that the use of backorders to approximate aircraft availability is not adequate. The Dyna-METRIC model was developed after Mod-METRIC to accommodate for the dynamic requirements process (e.g. surge requirements in a war-time scenario) and the differing criticality of different spares (Mills, 1985:11).

Dyna-METRIC

Unless stated otherwise, all references from this subsection will come from a 1988 RAND Corporation report entitled, Dyna-METRIC Version 4 Modeling Worldwide Logistics Support of Aircraft Components. The authors were Karen E. Isaacson, Patricia Boren, Christopher L. Tsai and Raymond Pyles.

Developer(s): The Dyna-METRIC model has evolved as the result of several RAND Corporation projects dating back to the 1970's. R. J. Hillestad and M. J. Carrillo are credited with the "theoretical development of the dynamic queuing equations that form the heart of Dyna-METRIC Hillestad, 1982:5). The Headquarters Air Force Logistics Command Management Sciences Division (HQ AFLC/XPS) is responsible for the current version of the model (iii).

Model Purpose: Dyna-METRIC is a readiness, or availability, based model that "relates logistics resources and policies to wartime readiness" (V). It was developed for logisticians to assess the impact of "wartime dynamics and repair constraints and provides operational performance measures, problem detection, and spares requirements" (V). Dyna-METRIC will soon replace Mod-METRIC as the model used to determine whole engine and engine module requirements (both wartime and peacetime requirements). Additionally, code is currently being written to incorporate Dyna-METRIC into the Logistics Support Cost (LSC) model. This will change the LSC from a pure demand based approach to one that uses marginal analysis to maximize improvements in *availability* per dollar spent (Niklas, 1991). Dyna-METRIC allows one to model three echelons of maintenance repair and three indenture levels of components (V).

Model Algorithm: Dyna-METRIC allows one to predict the number of aircraft components that are flowing from point to point in the repair process (i.e., through repair

"pipelines"). Central to these predictions is the delay or processing time these components must spend in each pipeline segment. "The expected number of components in each segment, then, depends on the rate at which demands occur and the time the components spend in each segment" (VI).

Dyna-METRIC uses the user-supplied pipeline variance to mean ratio (VTMR) to determine what type of distribution to use to predict the number of components within a pipeline segment. A VTMR of less than one corresponds to a binomial distribution. A VTMR of one suggests a poisson distribution, and a VTMR of greater than one suggest a negative binomial distribution. These distributions are used by the model to "recommend stock levels for components" and "to predict performance at each base for each time of analysis" (92).

Unlike Mod-METRIC, Dyna-METRIC also allows one to consider policies of full and partial cannibalization of aircraft. The full cannibalization routine involves two assumptions. First, it assumes that all the aircraft at a base look alike (i.e., composed of the same LRUs) and will lead to overly optimistic results if this assumption is violated. The second assumption is that "cannibalization can be done instantly and without consuming resources" (95). When either of the above assumptions are broken, it is recommended that, if one wants to include cannibalization in one's model, a partial cannibalization policy is modeled in lieu of the full cannibalization routine (94-95).

It is beyond the scope of this appendix to introduce the numerous mathematical equations utilized by Dyna-METRIC. Interested readers should consult the reference listed at the beginning of this model's analysis.

Data Inputs: The Dyna-METRIC model requires numerous user inputs. The following is a partial list of these inputs:

* Expected pipeline size (i.e., component quantity) at the location being analyzed
* Pipeline Variance to Mean Ratio (VTMR)
* Component stock level
* Number of aircraft at the base, after attrition
* Number of different types of LRU of which the aircraft are constructed
* Quantity per application of LRU i
* Quantity per application of LRU i that must be operational if the aircraft is fully mission capable (FMC)
* LRU i stock level at base (92-93)

Assessment: Dyna-METRIC's ability to predict logistics requirements under dynamic conditions has made it a valuable tool. Early uses of the model are numerous. Ogden Air Logistics Center used the model to study F-4 and F-16 aircraft readiness and supportability. Headquarters Air Force Logistics Command used it to study F100 engine requirements, and the Tactical Air Command has used it to analyze the impact of different repair and supply strategies on F-15 readiness and deployability (Hillestad, 1982:iv).

Dyna-METRIC is not without its limitations, however. Although the model allows one to model multiple bases, this capability is weakened because the model can not handle multiple types of collocated aircraft. Additionally,

lateral supply and flight line constraints are also "not explicitly modeled" (V).

A 1988 RAND Corporation report questions the ability of models such as Dyna-METRIC to model the "failure process and the resulting series of random demands on supply and maintenance" (Crawford, 1988:V). Specifically, those models which assume that component removals follow a Poisson arrival process "assume the flow of broken parts ('demand process') into the repair facility will be random, but with a certain mean and a certain degree of randomness or 'irregularity' (Crawford, 1988:4). The variance-to-mean ratio (VTMR) is a measure of this variability and thus the unpredictability of the demand process. Crawford's findings show that actual VTMRs experienced are significantly greater than those assumed by the models (such as Dyna-METRIC) (Crawford, 1988:1). When this happens, "the part will arrive at the repair process in what appear to be large random clusters instead of random, but more evenly spaced, intervals" (4). These results, according to Crawford, reduce the confidence one can place in these models and may have a "damaging effect on aircraft availability and wartime readiness" (Crawford, 1988:vi).

Dyna-METRIC also fails to identify the least cost mix of LRUs and SRUs needed to satisfy availability goals. The Aircraft Sustainability Model (ASM)) was developed by the Logistics Management Institute (LMI) to correct this problem (Oster, Sakulich, and Stone, 1989:2).

Appendix D. Condemnations CER Database

The data in Table 21 represents the entire database used in the development of condemnation CERs for this thesis. The data comes from numerous sources. The annual condemnation costs, number of aircraft, and annual flying hours were all obtained from the Weapon System Cost Retrieval System (HO36C).

The annual sorties and annual landings were obtained from what is currently referred to as Acquisition Logistics Division (ALD) Pamphlet 800-4, Acquisition Management Aircraft Historical Reliability and Maintainability Data. Because ALD has been known by different names through the years, the different volumes of 800-4 have different titles. The first three volumes were labeled AFALD Pamphlet 800-4. Sorties and landings data from FY75 through the first half of FY78 was taken from Volume I. Data from the second half of FY78 through FY80 came from Volume II, and data from FY81 through the first half of FY83 came from Volume III. The next two volumes were known as the Air Force Acquisition Logistics Center (AFALC) Pamphlet 800-4. Data from the second half of FY83 through FY85 came from Volume IV, and data from FY86 through FY87 came from Volume V. Finally, data from FY88 to FY89 came from Volume VI, known as ALD Pamphlet 800-4.

The remaining physical and performance characteristics data was taken from various addenda to AFG 2, Standard

Aircraft Characteristics. Data for the F-4D and F-4E came from Addendum 55, Volume 1. Data for the C-5A came from Addendum 53, Volume 2. Data for the C-130B and T-38A came from Addendum 54, Volume 2. Data for the F-16A came from Addendum 58, Volume 1. Data for the A-7D, A-7K, KC-135A, and A-10A came from Addendum 59, Volume 1. Data for the T-37B, C-130E, and C-141B came from Addendum 56, Volume 2. Data for the F-15A and F-15B came from September 1989 Standard Aircraft Characteristics pamphlets (no AFG references were found on these pamphlets). Finally, the B-52G, B-52H, F-111D, and FB-111A data was taken from Addendum 60, Volume 1.

Table 21

Condemnations CER Database

MDS	FY	ANNUAL CONDEMN COSTS	# OF A/C	ANNUAL FLY HRS	ANNUAL # OF SORTIES	ANNUAL # OF LANDINGS	DUMY	EMPTY WEIGHT
F15A	85	56,284,486	321	71,586			0	26,749
F15A	86	46,541,266	318	75,559			0	26,749
F15A	87	46,559,725	317	74,363			0	26,749
F15A	88	46,305,459	314	69,722			0	26,749
F15A	89	39,983,476	313	71,684			0	26,749
F15B	85	9,949,506	54	12,691			0	26,832
F15B	86	8,634,666	54	14,114			0	26,832
F15B	87	9,087,565	53	14,327			0	26,832
F15B	88	8,948,457	54	13,495			0	26,832
F15B	89	7,364,837	53	13,382			0	26,832
F16A	85	62,780,304	627	171,748	125,503	127,526	0	15,306
F16A	86	60,804,303	619	168,671	126,265	127,488	0	15,306
F16A	87	67,173,261	615	175,137	134,365	138,092	0	15,306
F16A	88	61,454,897	604	167,914	112,759	113,563	0	15,306
F16A	89	55,416,270	563	165,706	112,336	113,021	0	15,306
F4D	76	15,609,443	494	104,756	68,020		0	28,873
F4D	77	13,008,510	472	101,750	70,210		0	28,873
F4D	78	17,001,188	467	96,590	72,091		0	28,873
F4D	79	20,153,467	456	100,067	77,301	91,781	0	28,873
F4D	80	22,737,395	450	89,927	69,192	86,888	0	28,873
F4E	77	13,565,579	697	168,900	121,195		0	30,328
F4E	78	19,369,172	671	158,431	119,474		0	30,328
F4E	79	18,444,521	626	155,493	119,391	144,590	0	30,328
F4E	80	19,210,958	546	129,388	101,179	114,328	0	30,328
F4E	81	24,254,355	499	113,343	89,376	98,232	0	30,328
A7D	76	13,370,606	407	82,159	51,267		0	19,733
A7D	77	9,251,047	406	109,914	64,787		0	19,733
A7D	78	14,151,911	384	101,421	61,127		0	19,733
A7D	79	13,002,152	376	94,101	59,537	59,903	0	19,733
A7D	80	13,564,173	371	91,423	59,985	60,285	0	19,733
A7K	83	1,251,303	31	8,292			0	21,300
A7K	84	1,057,256	31	8,630			0	21,300
A7K	85	1,179,063	29	8,122	5,520	5,533	0	21,300
A7K	86	1,145,533	30	6,040	4,159	4,181	0	21,300
A7K	87	919,806	30	6,583	4,450	4,464	0	21,300
A10A	84	17,683,981	668	226,171			0	21,541
A10A	85	18,505,945	663	222,569	132,998	133,776	0	21,541
A10A	86	22,482,695	659	219,958	132,998	133,314	0	21,541
A10A	87	26,952,091	651	224,177	134,048	134,057	0	21,541
A10A	88	22,279,258	627	211,892	128,100	128,119	0	21,541
F111D	78	13,729,867	90	15,140	6,335		0	46,949
F111D	79	13,600,558	85	17,270	7,416	11,288	0	46,949

Table 21 (Continued)

Condemnations CER Database

MDS	FY	ANNUAL CONDEMN COSTS	# OF A/C	ANNUAL FLY HRS	ANNUAL # OF SORTIES	ANNUAL # OF LANDINGS	DUMY	EMPTY WEIGHT
F111D	80	15,719,180	84	17,828	8,152	12,108	0	46,949
F111D	81	14,234,373	83	17,906	7,811	11,609	0	46,949
F111D	82	13,848,110	82	16,933	7,666	11,678	0	46,949
T37B	76	5,344,323	749	255,018	208,570		0	4,067
T37B	77	4,247,758	680	273,220	219,115		0	4,067
T37B	78	6,278,631	697	255,861	94,961		0	4,067
T37B	79	7,757,701	668	288,414	229,489	790,846	0	4,067
T37B	80	5,521,700	649	288,141	231,083	798,415	0	4,067
T38A	75	15,501,426	990	404,275	338,665		0	7,410
T38A	76	10,235,854	984	309,753	247,519		0	7,410
T38A	77	13,817,793	916	338,751	278,209		0	7,410
T38A	78	14,497,282	819	305,805	119,751		0	7,410
T38A	79	18,747,947	777	312,855	257,550	829,486	0	7,410
B52G	76	35,158,761	174	69,194	9,335		1	180,041
B52G	77	49,605,497	172	65,512	8,496		1	180,041
B52G	78	52,700,602	173	64,269	8,324		1	180,041
B52G	79	56,680,050	173	65,013	9,042	25,617	1	180,041
B52G	80	54,222,043	173	63,713	9,705	27,839	1	180,041
B52H	76	16,499,476	97	36,635	4,920		1	184,291
B52H	77	20,263,183	97	36,346	4,543		1	184,291
B52H	78	21,980,774	96	36,513	4,567		1	184,291
B52H	79	22,330,298	96	36,691	5,075	15,055	1	184,291
B52H	80	22,374,407	95	36,430	5,103	13,971	1	184,291
C5A	76	37,813,318	73	36,710	7,252		1	320,085
C5A	77	34,824,717	77	48,590	9,948		1	320,085
C5A	78	41,647,986	75	48,282	4,693		1	320,085
C5A	79	44,176,326	77	48,657	10,222	31,690	1	320,085
C5A	80	46,922,447	77	51,133	10,570	32,389	1	320,085
C130B	76	3,968,334	97	37,811	14,905		1	72,300
C130B	77	2,893,091	94	36,585	14,208		1	72,300
C130B	78	2,738,158	93	37,836	18,398		1	72,300
C130B	79	2,781,287	94	36,923	19,536	50,361	1	72,300
C130B	80	4,587,832	9[illegible]	37,621	20,285	52,571	1	72,300
C130E	76	16,066,401	338	169,480	74,174		1	73,804
C130E	77	12,798,896	309	162,304	66,747		1	73,804
C130E	78	12,935,999	280	164,117	90,682		1	73,804
C130E	79	12,414,932	27[illegible]	161,280	96,839	225,448	1	73,804
C130E	80	18,359,622	276	162,342	99,644	234,637	1	73,804
C141B	82	50,958,201	269	262,960	73,405	161,239	1	140,882
C141B	83	55,749,449	268	289,119	87,879	177,036	1	140,882
C141B	84	53,723,129	268	290,509			1	140,882
C141B	85	39,329,435	267	290,142	89,976	184,982	1	140,882
C141B	86	44,991,514	266	289,039	88,977	187,656	1	140,882

Table 21 (Continued)

Condemnations CER Database

MDS	FY	ANNUAL CONDEMN COSTS	# OF A/C	ANNUAL FLY HRS	ANNUAL # OF SORTIES	ANNUAL # OF LANDINGS	DUMY	EMPTY WEIGHT
KC135A	75	57,757,551	607	220,148	47,430		1	97,030
KC135A	76	41,902,937	606	205,175	39,807		1	97,030
KC135A	77	60,962,617	599	189,271	43,958		1	97,030
KC135A	78	70,731,943	598	193,618	47,549		1	97,030
KC135A	79	81,852,238	587	193,084	49,601	157,466	1	97,030
FB111A	76	10,251,819	74	16,886	3,892		0	47,481
FB111A	77	10,123,838	70	18,469	4,870		0	47,481
FB111A	78	16,176,540	68	15,839	4,566		0	47,481
FB111A	79	13,769,682	67	18,286	5,416	9,295	0	47,481
FB111A	80	19,071,741	66	17,443	5,418	10,491	0	47,481

Table 21 (Continued)

Condemnations CER Database

MDS	THRUST PER ENGINE	ENG	LENGTH PLUS SPAN	MAX SPEED	TAKEOFF WEIGHT	MAX LOAD FACTOR	MAX CLIMB RATE	MAX COMBAT RADIUS
F15A	23,830	2	106.56	1,309	56,000	7.33	61,340	515
F15B	23,830	2	106.56	1,309	56,000	7.33	59,930	502
F16A	23,830	1	82.28	1,181	35,400	9	60,288	693
F4D	17,000	2	96.6	1,210	59,483	6.5	55,600	783
F4E	17,900	2	101.4	1,245	61,795	7.75	49,800	741
A7D	14,250	1	84.8	608	39,325	7	8,000	600
A7K	14,500	1	87.42	569	42,000	7	9,485	282
A10A	9,065	2	110.5	362	49,774	7.33	6,203	351
F111D	20,840	2	136.47	1,262	100,000	7	45,000	1,270
T37B	1,025	1	63.1	357	6,800	6.67	3,600	167
T38A	3,850	2	71.6	709	11,761	7.33	33,300	305
B52G	13,750	8	346.9	549	488,000	2	8,243	3,118
B52H	17,000	8	345.3	547	488,000	2	9,628	3,747
C5A	40,805	4	470.5	495	769,000	2.5	5,580	2,519
C130B	9,388	4	230.4	330	135,000	3	4,420	1,549
C130E	9,388	4	230.4	317	175,000	3	4,060	1,866
C141B	21,000	4	328.4	493	323,100	2.5	6,300	2,366
KC135A	13,750	4	267.00	527	300,800	2.00	6,350	1,613
FB111A	20,350	2	145.54	1,262	119,243	3.00	33,800	

Appendix E. Model Validation Database

The following table provides the data used in both the validation and sensitivity tests. Data included in Table 22 taken from the same sources used in Table 21.

Table 22

Model Validation Database

MDS	CONDEMN COSTS	FY	# OF MDS	ANNUAL FLY HRS	FLY HRS PER AC	# OF SORTIES
F16A	27,537,555	1983	514	118,018	229.61	85,379
F4D	24,151,890	1981	445	89,844	201.90	68,869
F4E	24,254,355	1981	499	113,343	227.14	89,376
A7D	20,075,237	1981	360	83,120	230.89	56,073
A7K	1,560,822	1988	30	7,381	246.03	4,874
A10A	12,012,017	1989	586	218,690	373.19	126,809
F111D	14,831,043	1983	82	18,368	224.00	8,406
B52G	43,909,467	1981	172	63,959	371.85	9,465
B52H	20,415,995	1981	96	37,873	394.51	5,226
C5A	71,036,363	1981	77	52,160	677.40	10,373
C130B	4,698,837	1981	91	36,443	400.47	20,310
C130E	18,837,210	1981	279	168,526	604.04	99,436
C141B	51,264,650	1987	267	284,065	1,063.91	87,102
FB111A	13,471,819	1981	63	17,332	275.11	5,513

Table 22 (Continued)

Model Validation Database

MDS	FLY HRS PER SORTY	THRUST PER ENGINE	TAKEOFF WEIGHT / EMPTY WEIGHT	FLYAWAY COST	MAX SPEED	MAX LOAD FACTOR
F16A	1.38	23,830	2.31	11,646,586	1,181	9.00
F4D	1.30	17,000	2.06	8,433,735	1,210	6.50
F4E	1.27	17,900	2.04	10,140,562	1,245	7.75
A7D	1.48	14,250	1.99	8,734,940	608	7.00
A7K	1.51	14,500	1.97	16,767,068	569	7.00
A10A	1.72	9,065	2.31	8,734,940	362	7.33
F111D	2.19	20,840	2.13	39,859,438	1,262	7.00
B52G	6.76	13,750	2.71	54,819,277	549	2.00
B52H	7.25	17,000	2.65	60,240,964	547	2.00
C5A	5.03	40,805	2.40	139,959,839	495	2.50
C130B	1.79	9,388	1.87	18,172,691	330	3.00
C130E	1.69	9,388	2.37	10,943,775	317	3.00
C141B	3.26	21,000	2.29	34,437,751	493	2.50
FB111A	3.14	20,350	2.37	39,658,635	1262	3.00

Appendix F. Model Sensitivity Test Results

Table 23

Model Sensitivity Test Results

"SORT" Variable Multiplied by 1.2

MDS	NEW LINEAR ESTIMATE	NEW EST./ ORIG. EST.	NEW ARITHMETIC ESTIMATE	NEW EST./ ORIG. EST.
F16A	42,377,500	1.06	41,424,889	1.06
F4D	20,732,006	1.11	20,364,706	1.11
F4E	24,314,651	1.12	23,999,556	1.12
A7D	12,487,371	1.15	12,469,575	1.15
A7K	2,622,908	1.06	3,264,162	1.04
A10A	34,227,437	1.12	31,527,170	1.13
F111D	17,116,714	1.01	17,239,688	1.01
B52G	36,356,178	1.01	35,914,610	1.01
B52H	36,263,284	1.00	35,856,568	1.00
C5A	50,712,950	1.01	51,933,888	1.01
C130B	(4,617,817)	0.88	(3,648,991)	0.86
C130E	32,373,571	1.10	29,873,545	1.10
C141B	38,679,337	1.07	37,494,591	1.07
FB111A	27,094,876	1.01	26,468,474	1.01

"SORT" Variable Multiplied by .8

MDS	NEW LINEAR ESTIMATE	NEW EST./ ORIG. EST.	NEW ARITHMETIC ESTIMATE	NEW EST./ ORIG. EST.
F16A	37,282,081	0.94	36,588,133	0.94
F4D	16,621,904	0.89	16,463,249	0.89
F4E	18,980,691	0.88	18,936,369	0.88
A7D	9,140,934	0.85	9,293,016	0.85
A7K	2,332,028	0.94	2,988,048	0.96
A10A	26,659,475	0.88	24,343,387	0.87
F111D	16,615,044	0.99	16,763,485	0.99
B52G	35,791,307	0.99	35,378,414	0.99
B52H	35,951,397	1.00	35,560,513	1.00
C5A	50,093,889	0.99	51,346,253	0.99
C130B	(5,829,918)	1.12	(4,799,561)	1.14
C130E	26,439,330	0.90	24,240,454	0.90
C141B	33,481,089	0.93	32,560,226	0.93
FB111A	26,765,860	0.99	26,156,160	0.99

Table 23 (Continued)

Model Sensitivity Test Results

"THRUST" Variable Multiplied by 1.2

MDS	NEW LINEAR ESTIMATE	NEW EST./ ORIG. EST.	NEW ARITHMETIC ESTIMATE	NEW EST./ ORIG. EST.
F16A	44,823,135	1.13	44,443,737	1.14
F4D	22,239,140	1.19	22,292,820	1.21
F4E	25,398,441	1.17	25,552,156	1.19
A7D	13,800,101	1.28	14,132,678	1.30
A7K	5,515,802	2.23	6,434,530	2.06
A10A	32,342,939	1.06	30,003,614	1.07
F111D	21,232,698	1.26	21,756,592	1.28
B52G	38,954,921	1.08	38,783,811	1.09
B52H	39,669,525	1.10	39,587,384	1.11
C5A	58,953,710	1.17	60,950,435	1.18
C130B	(3,256,703)	0.62	(2,082,242)	0.49
C130E	31,373,665	1.07	29,199,033	1.08
C141B	40,480,559	1.12	39,818,921	1.14
FB111A	31,194,512	1.16	30,955,520	1.18

"THRUST" Variable Multiplied by .8

MDS	NEW LINEAR ESTIMATE	NEW EST./ ORIG. EST.	NEW ARITHMETIC ESTIMATE	NEW EST./ ORIG. EST.
F16A	34,836,446	0.87	33,569,286	0.86
F4D	15,114,770	0.81	14,535,134	0.79
F4E	17,896,900	0.83	17,383,769	0.81
A7D	7,828,204	0.72	7,629,912	0.70
A7K	(560,866)	(0.23)	(182,320)	(0.06)
A10A	28,543,974	0.94	25,866,942	0.93
F111D	12,499,060	0.74	12,246,581	0.72
B52G	33,192,563	0.92	32,509,212	0.91
B52H	32,545,156	0.90	31,829,698	0.89
C5A	41,853,129	0.83	42,329,706	0.82
C130B	(7,191,031)	1.38	(6,366,310)	1.51
C130E	27,439,337	0.93	24,914,965	0.92
C141B	31,679,867	0.88	30,235,897	0.86
FB111A	22,666,224	0.84	21,669,114	0.82

Table 23 (Continued)

Model Sensitivity Test Results

TOEMPWT and TOEMPWT2
Multiplied by 1.2

MDS	NEW LINEAR ESTIMATE	NEW EST./ ORIG. EST.	NEW ARITHMETIC ESTIMATE	NEW EST./ ORIG. EST.
F16A	60,945,609	1.53	61,293,680	1.57
F4D	37,486,025	2.01	36,097,700	1.96
F4E	40,250,368	1.86	38,765,765	1.81
A7D	29,008,730	2.68	27,428,438	2.52
A7K	20,480,102	8.27	19,325,961	6.18
A10A	51,539,598	1.69	50,180,931	1.80
F111D	36,312,315	2.15	35,904,080	2.11
B52G	60,815,791	1.69	66,245,733	1.86
B52H	60,301,595	1.67	64,967,814	1.82
C5A	72,315,197	1.43	75,639,133	1.46
C130B	11,849,059	(2.27)	10,345,571	(2.45)
C130E	51,044,381	1.74	50,459,835	1.86
C141B	56,987,700	1.58	56,876,972	1.62
FB111A	48,578,704	1.80	49,737,775	1.89

TOEMPWT and TOEMPWT2
Multiplied by .8

MDS	NEW LINEAR ESTIMATE	NEW EST./ ORIG. EST.	NEW ARITHMETIC ESTIMATE	NEW EST./ ORIG. EST.
F16A	18,713,972	0.47	20,771,555	0.53
F4D	(132,115)	(0.01)	3,945,477	0.21
F4E	3,044,973	0.14	7,315,216	0.34
A7D	(7,380,425)	(0.68)	(2,657,276)	(0.24)
A7K	(15,525,166)	(6.27)	(10,128,323)	(3.24)
A10A	9,347,314	0.31	9,734,289	0.35
F111D	(2,580,557)	(0.15)	1,535,910	0.09
B52G	11,331,694	0.31	10,610,785	0.30
B52H	11,913,086	0.33	11,769,135	0.33
C5A	28,491,642	0.57	32,004,474	0.62
C130B	(22,296,794)	4.27	(16,145,060)	3.82
C130E	7,768,621	0.26	7,909,225	0.29
C141B	15,172,725	0.42	17,150,493	0.49
FB111D	5,282,032	0.20	7,146,033	0.27

Appendix G. Demand Volatility Analysis Database

The tables presented in Appendix G provide the data used to perform the demand volatility analysis. Table 24 and 25 provide the actual data used in the analysis. Table 26 provides the original replenishment spares database. It is in then year dollars and the engine spares and common spares pools have not been distributed. Table 27 provides the inflation rates used to adjust the figures in Table 26 to FY91 constant dollars. Table 28 shows what percentage of the engine hours were associated with the F-15 and F-16 aircraft and then shows how this data was used to determine how the engine spares pool would be distributed between the F-15 and F-16. Finally, Table 29 provides the common spares allocation factors used to distribute the common spares pool among the MD.

Several sources were used to obtain the data. The condemnations and engine hours data was obtained from the Weapon System Cost Retrieval System (WSCRS). The orignal replenishment spares requirements data was obtained from unpublished records maintained by HQ AFLC/FMBSR. The common spares distribution factors were obtained from Ms. Virginia Mattern of the Logistics Management Institute (LMI). Finally, the inflation factors were obtained from AFR 173-13, US Air Force Cost and Planning Factors.

Table 24

Condemnations Data

MD	FY84	FY85	FY86	FY87	FY88	FY89	FY90
A7	10,897,726	12,525,627	15,927,168	12,704,698	15,021,421	14,557,360	9,924,637
A10	17,685,639	18,505,945	22,482,695	26,952,091	22,801,991	12,678,766	21,080,539
B52	67,802,308	65,525,255	96,822,448	68,554,314	49,764,888	60,380,663	87,297,382
FB111	15,029,992	15,397,625	17,660,118	16,365,413	11,200,087	8,388,055	10,462,112
F111	77,283,959	94,721,506	143,471,116	98,783,317	78,529,343	66,266,681	78,367,448
C5	58,941,558	69,644,836	47,507,746	60,373,018	30,780,199	34,100,719	39,529,038
C130	53,029,199	48,532,383	47,203,615	52,324,771	37,130,950	44,257,693	45,339,949
C135	74,261,499	70,890,978	113,535,565	69,487,864	41,380,030	66,406,564	57,442,725
C141	53,903,812	39,438,923	45,133,599	51,455,810	38,340,884	35,797,328	39,265,029
F4	79,509,217	65,004,530	71,277,687	62,292,829	41,471,113	38,428,604	37,291,205
F15	94,229,381	141,948,791	119,690,241	126,743,651	125,738,650	111,866,090	140,222,539
F16	50,193,007	77,297,891	86,523,390	103,671,647	107,687,604	112,087,021	111,550,471
T37	7,517,658	9,845,171	6,916,134	10,050,722	3,289,977	5,803,357	6,346,410
T38	26,402,486	31,876,042	26,950,630	24,989,937	27,673,083	24,036,235	13,618,315
TOTAL	686,687,441	761,155,503	861,102,152	784,750,082	630,810,220	635,055,136	697,737,799

Table 25

Replenishment Spares Requirements Data

MD	FY82	FY83	FY84	FY85	FY86	FY87	FY88
A7	98,172,633	80,511,860	40,579,612	32,686,854	16,464,560	18,512,541	16,862,638
A10	170,224,384	180,521,848	137,978,155	118,633,803	55,248,758	53,360,532	50,318,092
B52	362,071,984	570,397,004	318,602,427	222,520,423	153,490,293	62,714,929	68,676,611
FB111	53,734,630	79,448,190	35,873,058	24,716,197	13,556,659	19,949,566	470,292
F111	505,610,117	586,498,127	337,447,087	264,827,230	177,186,456	280,392,671	245,559,718
C5	573,740,467	192,176,030	122,303,641	59,685,681	92,599,549	139,183,822	158,487,748
C130	191,532,425	121,650,437	138,968,204	154,642,019	122,663,205	78,311,292	66,214,526
C135	182,820,752	188,721,598	127,276,699	191,067,136	164,320,542	124,539,414	150,232,242
C141	163,825,681	165,202,247	115,941,019	105,202,582	48,586,907	85,759,609	57,882,909
F4	407,893,385	387,414,482	265,754,854	130,288,498	77,822,122	70,442,834	48,926,236
F15	826,827,347	633,518,624	466,103,676	423,885,452	394,443,587	504,650,484	492,486,778
F16	258,488,088	261,216,707	238,851,421	589,373,469	399,062,508	370,717,811	474,706,412
T37	39,040,208	34,332,085	14,563,107	84,389,671	12,732,731	6,400,651	2,830,302
T38	136,700,389	153,823,970	110,142,233	39,330,282	39,030,700	22,108,415	25,789,948
TOTAL	3970682490	3635433208	2470385194	2441299296	1767208578	1837044571	1859444453

Table 26

Original Replenishment Spares Requirements Data

MDS	FY82	FY83	FY84	FY85	FY86	FY87	FY88
A7	48.2	57.3	28.4	20.3	11.8	14.2	9.3
A10	81.9	114.4	101.1	84.3	37.8	43.9	46
B52	155.8	275.7	196.2	96.9	75.3	36.9	50.5
FB111	37.2	62.2	28.3	19.8	10.3	17.2	0
F111	357.4	459	270.5	220.6	155	255.2	232.6
C5	434.6	148.9	97	45.4	78.4	124.5	150
C130	123	84.5	93.1	100.3	87.4	53.3	51.8
C135	104.3	69.2	54.5	113.3	107.5	69.1	111.6
C141	53	36.7	43.9	56.5	16	46.7	34.1
F4	143.9	237.7	181.2	87.1	57.8	58.1	40.5
F15	284.1	192.8	182.8	93.8	62.6	157.9	224.4
F16	59.7	61.5	77	313.4	162.9	111.6	211.9
T37	30.1	27.5	12		7.5	3.5	1.6
T38	77.2	31.9	42.9		30.8	15.5	20.7
F100	409.8	421.4	285.4	397.8	453.7	493.7	380.9
F110	0	0	0	0	66.9	107.7	155.8
COMM	704.9	719	419.8	419.4	276	239.5	265.3
TOT	3105.1	2999.7	2114.1	2140.8	1697.7	1848.5	1987.0

Table 27. Inflation Factors

FY82	FY83	FY84	FY85	FY86	FY87	FY88
.771	.801	.824	.852	.886	.921	.959

Table 28

Engine Spares Requirements Distribution

	FY82	FY83	FY84	FY85	FY86	FY87	FY88
F15	298,958	327,872	353,232	363,792	389,576	385,474	360,181
F15A							
F15B							
F15D						2,907	3,936
F15C					1,802	19,855	37,977
F15E							838
SUB	298,958	327,872	353,232	363,792	391,378	408,236	402,932
F16	95,755	137,843	194,490	211,820	242,284	268,076	271,992
F16B							
F16C						2,442	6,255
F16D						419	299
SUB	95,755	137,843	194,490	211,820	242,284	270,937	278,546
TOT	394,713	465,715	547,722	575,612	633,662	679,173	681,478
F15%	0.76	0.70	0.64	0.63	0.62	0.60	0.59
F15 SHARE	310.38	296.67	184.06	251.41	280.23	296.75	225.21
F16 SHARE	99.42	124.73	101.34	146.39	173.47	196.95	155.69

Table 29

LMI Common Spares Distribution Factors

	FY82	FY83	FY84	FY85	FY86	FY87	FY88
A7	3.9	1	1.2	1.8	1.0	1.2	2.6
A10	7.0	4.2	3.0	4.0	4.0	2.2	0.9
B52	17.5	25.2	15.8	22.1	22.0	8.7	5.8
FB111	0.6	0.2	0.3	0.3	0.6	0.5	0.2
F111	4.6	1.5	1.8	1.2	0.7	1.3	1.1
C5	1.1	0.7	0.9	1.3	1.3	1.5	0.8
C130	3.5	1.8	5.1	7.5	7.7	7.9	4.4
C135	5.2	11.4	12	11.8	13.8	19.0	12.2
C141	10.4	13.3	12.3	7.9	9.8	13.5	8.1
F4	24.2	10.1	9	5.7	4.0	2.8	2.4
F15	6.1	2.5	4.1	3.8	2.4	4.2	8.6
F16	5.7	3.2	4.4	10.1	6.2	13.7	33.0
T37					1.4	1.0	0.4
T38	4.0	12.7	11.4		1.4	2.0	1.5

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13. ABSTRACT (Maximum 200 words)

This thesis covers three objectives: 1) develop a background reference document concerning recoverable spares cost estimating; 2) evaluate a representative sample of existing spares cost models; and 3) use aircraft physical and performance characteristics to develop a model for estimating annual replenishment spares costs. A condemnations cost estimating relationship (CER) was developed first and then both a CER and spreadsheet generated factors which related condemnations to replenishment spares costs were developed. For the condemnations CER, only logarithmic transformations provided statiscally acceptable results, and even these models exhibited wide prediction intervals due to the large amount of variability in the CER databases (as evidenced by the number of outliers). The CER relating condemnations to replenishment spares costs was a poorer statistical performer. Spreadsheet generated factors showed that the ratio of replenishment spares requirements to condemnations exhibited a downward trend across the data years. 25) * logistics support,)

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